

AD-A091 598

WASHINGTON UNIV SEATTLE DEPT OF PSYCHOLOGY
INDIVIDUAL DIFFERENCES IN ATTENTION.(U)
SEP 80 E HUNT, M LANSMAN

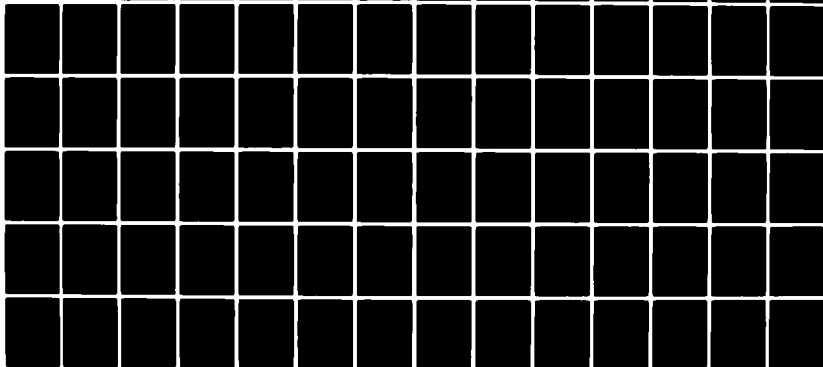
F/6 5/10

UNCLASSIFIED

N00014-77-C-0225
NL

1 1 1
AL
ALVAB-2

EP



END
DATE
FILMED
12-80
DTIC

AD A091598

LEVEL II

(12) ^{fw}

(6) Individual Differences in Attention

(10) Earl/Hunt and Marcy/Lansman

Department of Psychology
University of Washington
Seattle, Washington 98195

DTIC
ELECTE
NOV 05 1980

(11) Sep 74

(12) 82

E

(9) Technical Report No. 8, 1 Apr 79-31 Mar 80,
September, 1980

This research was sponsored by:

Personnel and Training Research Programs
Psychological Sciences Divisions
Office of Naval Research

Under Contract No. N00014-77-C-0225

Contract Authority Identification Number, NR 154-398

(15)

(16)

RR042-06

Approved for public release; distribution unlimited.

(17)

RR042-06-01

Reproduction in whole or in part is permitted
for any purpose of the U. S. Government

DDC FILE COPY

387 763
80 11 04 027

Individual Differences in Attention

Earl Hunt and Marcy Lansman

University of Washington

Accession For	
NTIS GRA&I	
DDC TAB	
Unannounced	
Justification	
By	
Distribution/	
Availability Codes	
Dist.	Avail and/or special
A	

Running head: Attention

Send proofs to: Earl Hunt
Department of Psychology NI-25
University of Washington
Seattle, WA 98195

Unclassified

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER NR 154-398 Report No. 8 ✓	2. GOVT ACCESSION NO. AD-A091598	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) Individual Differences in Attention		5. TYPE OF REPORT & PERIOD COVERED Interim April 1, 1979-March 31, 1980
		6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s) Earl Hunt and Marcy Lansman		8. CONTRACT OR GRANT NUMBER(s) N00014-77-C-0225 ✓
9. PERFORMING ORGANIZATION NAME AND ADDRESS Department of Psychology NI-25 University of Washington Seattle, Washington 98195 ✓		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS 61153N RR 042-06; RR 042-06-01 NR 154-398
11. CONTROLLING OFFICE NAME AND ADDRESS Personnel and Training Research Programs Office of Naval Research (Code 458) Arlington, Virginia 22217		12. REPORT DATE September, 1980
		13. NUMBER OF PAGES 68
14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office)		15. SECURITY CLASS. (of this report) Unclassified
		15a. DECLASSIFICATION DOWNGRADING SCHEDULE
16. DISTRIBUTION STATEMENT (of this Report) Approved for public release; distribution unlimited		
17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)		
18. SUPPLEMENTARY NOTES		
19. KEY WORDS (Continue on reverse side if necessary and identify by block number) information theory, dual tasks, secondary tasks, attention, individual differences		
20. ABSTRACT (Continue on reverse side if necessary and identify by block number) This paper examines the implications of a simple "resource competition" model of attention (Kahneman, 1973) for individual differences in performance in dual task situations. According to the model, an individual's performance on any task is determined by two factors: (a) the general mental resources available for that task, and (b) the efficiency of specific structures necessary to perform the task. In order to predict performance, information		

DD FORM 1 JAN 73 1473

EDITION OF 1 NOV 65 IS OBSOLETE
S/N 0102 LF 014 6601

Unclassified

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

Unclassified

SECURITY CLASSIFICATION OF THIS PAGE(When Data Entered)

→ about each of these factors is necessary.

This general model is discussed with respect to data obtained in the "easy-to-hard paradigm." In this paradigm, subjects are asked to perform an easy primary task in conjunction with a secondary task. Performance on both the easy primary task and the secondary task are used to predict performance on a harder version of the primary task. The principles of formal information theory are used to show that performance on the secondary task, done in conjunction with the easy primary task, should improve prediction of the hard primary task. Data from several experiments using the "easy-to-hard" paradigm support this conclusion.
↑

Unclassified

SECURITY CLASSIFICATION OF THIS PAGE(When Data Entered)

Individual Differences in Attention

People seldom concentrate their attention on a single activity. Drivers allow their minds to wander without driving into walls. The executive talking on three telephones at once may be fictional, but the airline traveler who reads while listening for flight announcements is real. Thinking about more than one thing at a time is a complex and important aspect of daily life.

When asked to explain complex behaviors, psychologists often try to break them down into their constituent elements. In factor analysis, performance on a complex test is depicted as a linear combination of basic abilities. A similar logic underlies Sternberg's (1977, 1979) technique of componential analysis. Sternberg's approach is to break complex problem solving behavior into stages, and to measure the processes involved in each stage. Problem solving, from this point of view, can be compared to the execution of a complex program with many subroutines. The program is to be understood by isolating the subroutines and measuring their capacities. A similar logic appears in our own research (Hunt, Frost, & Lunneborg, 1973; Hunt, Lunneborg, & Lewis, 1975), where we utilized what Pellegrino and Glazer (1979) have called the "cognitive correlates" approach. The basic idea behind this work was that human thought, as a form of information processing, must involve some basic information processing functions, analogous to the machine level operations (not the subroutines) of a digital computer (Hunt & Poltrock, 1974). Pure measures of these functions should be related to complex performance.

The assumption that has pervaded our work and that of others is that tasks done in isolation place the same demands on the information processing system as tasks done concurrently. This is the assumption we wish to question here. This assumption not only pervades the way we analyze data, but the way we collect it. We take great care to present people with just one problem at a time. But by concentrating on the ability to do things singly, we may miss a dimension of human behavior that is associated with the execution of concurrent tasks. The point has been made eloquently by H. A. Simon (1969) in his book, The Science of the Artificial. Simon observed that complex systems are often made up of simple subsystems. The complexity arises not from properties of the subsystems, but from their interaction. Hence we cannot hope to understand the operation of the large system simply by an analysis of the subsystems in isolation.

In this paper we shall look at a very simple model of dual task execution, a model in which each task is seen as competing for a general attentional resource. In such a model, the phrase "pay attention" is taken quite literally. The concept of an allocatable mental resource has received considerable attention in experimental psychology, but little effort has been made to formally apply the concept to individual differences research, or to discover how patterns of individual differences could be used to test models of resource allocation.

This presentation will be in four sections. The first contains a discussion of the concept of attentional resources as it has been developed by experimental psychologists. The second presents a formal model of the role of attentional resources in determining individual performance. The third section reports experimental results which pertain to this model. A closing

section deals with further implications of the basic ideas.

THE RESOURCE COMPETITION MODEL

Theory

According to the resource competition model, attention is akin to an energy resource, in that it can be parcelled out over concurrently executed tasks. The proposal has a long history in psychology. Posner (1978) cited relevant papers in the nineteenth century. Even Spearman's writings on the nature of general intelligence can be interpreted in terms of a general attentional resource. Kahneman (1973) has written the most comprehensive modern treatment, and we shall generally follow his analysis.

Consider any information processing task. By definition, the task involves the manipulation of signals being transmitted through the central nervous system. The manipulations must be carried out by specific structures. What happens when an information processing system executes two logically independent tasks concurrently? If the tasks require access to the same information processing structures, then the two tasks will interfere with each other. This is called structural interference.

Structural interference is obvious in many situations that require external sensors and effectors. We cannot look to the left and right simultaneously. Nor can we jump east and west. If the "structures" involved are central rather than peripheral, the interpretation is less obvious. For example, Baddeley and Hitch (1974) conducted a series of experiments in which people first memorized a list of digits, then attempted to comprehend sentences, and finally recited the digits. They found that digit memorization interfered with sentence comprehension. Baddeley and Hitch's interpretation was that the two tasks competed for space in a working memory

structure.

Other cases of inter-task interference are harder to explain in terms of competition for a structure, since it is not clear what structure is required by both tasks. Try to recite poetry while juggling! To account for non-structural interference, Kahneman (1973) proposed that all mental processes compete for a single pool of attentional resources. We will call this the resource competition model. Kahneman argued that attentional resources are analogous to a mental fuel that is drawn upon by virtually every mental activity. The availability of resources places a limit on the amount of mental processing that can take place at any one time.

Attentional resources are drawn upon by different mental structures in accordance with the demands that external tasks place upon them. The quantity of resources made available to a particular structure will depend upon the allocation policy that is in effect. An allocation policy determines how resources are to be distributed to the structures required by competing tasks. The allocation policy is based upon the total level of resources available (the capacity) and the expected payoff for varying levels of performance in each task. A resource competition model is not inconsistent with a structural model of inter-task interference, since the two types of models explain different situations. But how one analyzes people's ability to do several things at once does depend upon whether one believes that inter-task interference is primarily due to structural or to attentional resource competition.

Norman and Bobrow (1975) elaborated upon Kahneman's proposal by introducing several useful concepts. The first of these was the notion of a performance-resource function, a function that specifies the relationship

between the level of attentional resource supplied and the performance expected on a task. A hypothetical performance-resource function is shown in Figure 1, and will be used to illustrate Norman and Bobrow's ideas. An important point to remember is that Figure 1 does not represent the

Insert Figure 1 about here

relationship between two observables. It relates observable performance, p , to the conceptual but in principle unobservable variable, r , attentional resources. Symbolically, we shall refer to the function

$$(1) \quad p = f(r) .$$

Although we cannot observe f directly, we may place some restrictions upon it. First, providing more resources should never hurt performance. Therefore the first derivative, f' , should be non-negative

$$(2) \quad f'(r) \geq 0 .$$

Whenever f' is positive, an increase in resources will cause an increase in performance and, conversely, a decrease in resources will cause a decrease in performance. In such cases performance is said to be resource-limited. In Figure 1 performance is resource-limited from points A to B, and again from C to D. Whenever f' is zero, changing the resource level will not change performance, and performance is said to be data-limited.

The terms resource-limited and data-limited have appealing intuitive interpretations. One can easily think of tasks that seem to be resource-limited, i.e. tasks in which performance is determined by the extent to which we pay attention to what we are doing. Data limitations are equally easy to envisage. Most normal individuals can memorize two digits easily, and could not improve performance by paying more than the minimal amount of

attention required. As a more complex example, suppose that you are listening to a radio and that the transmission is masked by static. Your ability to comprehend the broadcast will be determined by the amount of attention you pay to it up to a certain point. Beyond that point, the signal-to-noise ratio becomes the limiting factor and performance becomes data-limited.

Data limitations are produced by the interaction between task requirements and personal capacities, and thus cannot be assigned to one or the other cause. In our radio broadcast example, we located data limitation in the radio transmitter. But people with different degrees of high frequency hearing loss would vary in the point at which they shifted from resource-limited performance (where they could comprehend more by paying more attention) to data-limited performance (where additional attention could not improve performance).

In spite of the heuristic value of examples, the concepts of resource and data limitation are strictly defined in terms of Equations (1) and (2), and, in the last analysis, are abstract relationships that can be only imperfectly represented in any concrete situation. The reason that the performance-resource function and its associated concepts must remain abstract is that we have no way of establishing a metric for r , the "amount of resources allocated."

Two indirect approaches to the measurement of resources have been attempted. One is to equate resource availability with a physiological concept, usually arousal. Resource output is then measured in terms of physiological status. Heart rate, cardiac deceleration, and dilation of the pupil of the eye have all been proposed as appropriate measures. Although these measures are interesting, the fact that they do not correlate

well with each other across situations makes their conceptual status problematical.

An alternative approach, which we have taken in our own research, is to use as an index of resource allocation the extent to which a task interferes with the execution of a second standard task. While the logic of this measurement technique does not depend upon Norman and Bobrow's analysis (see, for instance, the alternative treatment by Kerr, 1973), we shall use their terminology.

Imagine two abstract tasks, 1 and 2, that are to be done concurrently and that do not exhibit structural interference. Performance on the first task may be plotted as a function of performance on the second. Letting p_i be performance on the i th task ($i=1,2$), Norman and Bobrow refer to the function

$$(3) \quad p_1 = g(p_2)$$

as a performance operating characteristic (POC). Figure 2 presents an abstract POC, and will be used to illustrate some general features of these curves.

Insert Figure 2 about here

The form of a POC will be determined by the competition between tasks for attentional resources. Let R be total resource capacity and let r_1 and r_2 be the resources allocated to Tasks 1 and 2.

The resulting performance levels are

$$(4) \quad p_1 = f_1(r_1) \quad ; \quad p_2 = f_2(r_2),$$

with r_i subject to the restriction that

$$(5) \quad R = r_1 + r_2 .$$

Consider the horizontal section of the POC running from points A to B in Figure 2. This is evidence that Task 1 is data-limited at performance level p_1^* , since Task 2 performance increases in the A-B interval, without causing a drop in Task 1 performance. Since, by assumption, performance on a fixed task cannot increase without the commitment of more resources to it, some resources must have been diverted from Task 1 to Task 2 without causing a drop in performance. This is evidence that the performance-resource function for Task 1 is flat in the A-B region, i.e. at performance level p_1^* . By similar reasoning, the vertical segment of the POC, from points C to D, is evidence that Task 2 is data-limited and that Task 1 is resource-limited in the C-D interval. Finally, both Tasks 1 and 2 must be resource-limited in the B-C interval, as an increment in performance of one task is always accompanied by a decrement in performance in the other. What would happen if Tasks 1 and 2 were both data-limited? The POC would degenerate into a point defined by the intersection of a horizontal and vertical line.

The POC provides us with a method for determining the amount of resources required by an individual in order to reach a given level of performance on Task 1, when Task 1 has been designated as "primary" or most important to the performer. The experimenter specifies the external problem, establishes the desired level of performance on Task 1, and then measures the resource requirements of Task 1 by observing performance on the concurrent secondary task, Task 2. To illustrate, consider the following experiment. A performer is asked to memorize a short list of digits (Task 1) and then, while rehearsing those digits, to react to a probe signal, e.g. a light or tone (Task 2). After responding to the

probe, the performer must recall the digits. Suppose that the performance-resource function for rehearsing digits is as shown in Figure 3a. The number of digits one is capable of maintaining in memory increases with the resources deployed, up to the total resource capacity (R). We can re-plot this figure to show a family of curves: probability of correct recall as a function of resources applied to the task, with the curve parameter being the number of digits to be memorized. This is shown (for two and five digits) in Figure 3b. The goal is to measure the minimum amount of resources required to memorize one, two, three, four, or five digits, points A and B (for two and five) in Figure 3b. But, the abscissa of the performance-resource function refers to a hypothetical variable, r , that is, in principle, not open to direct observation.

 Insert Figure 3 about here

Performance on the probe reaction time task (Task 2) may be used to obtain the needed measure. The argument is that, under an appropriate payoff arrangement, a person should devote to the secondary task only those resources that are left over from the primary task. Thus performance on the secondary task provides a measure of the "spare capacity" left over after adequate resources have been devoted to the primary task. This procedure is valid only if the secondary task is resource-limited over the range of performance under consideration.

Continuing our example, suppose that the speed of reaction to a probe is a monotonically increasing function of the resources devoted to the reaction time task. The argument does not depend upon the form of the function, only upon the fact that the function satisfies the criterion for resource limitation, $f_2'(r) > 0$.

We then consider what POC will result when we combine the probe task with the task of memorizing two or five digits. Two possible POCs are shown in Figure 4. The key points in Figure 4 are the points A_2 and A_5 . These are the points at which the two memory tasks become data-limited.

 Insert Figure 4 about here

Since less resources are required to reach the data limitation point for the memorization of two than five digits, probe responding should be faster in the two digit than in the five digit condition.

What we are doing, then, is using performance on Task 2 as a measure of Task 1 resource requirements. Letting $p_2(2)$ and $p_2(5)$ be secondary task performance in the two and five digit memorization conditions, with an analogous notation for resources allocated, we have defined Task 2 resource requirements by

$$(6) \quad r_2(2) = f_2^{-1}(p_2(2)) ; \quad r_2(5) = f_2^{-1}(p_2(5)).$$

Since total resource capacity, R , is split between the two tasks, we can combine (5) with (6) to define $r_1(i)$, the amount of resources required to maintain i digits in memory, by

$$(7) \quad r_1(i) = R - f_2^{-1}(p_2(i)).$$

To what extent is this a scale? For the scale to be a linear or stronger measure of r we would have to make (and justify) some assumptions about f_2 . We shall discuss this in more detail later. For the present, we point out that the weak assumption that f is a performance-resource function and the much stronger assumption that R is constant over conditions are sufficient to ensure that $p_2(i)$ is an ordinal scale of $r_1(i)$. That is,

$$(8) \quad (p_2(i) > p_2(j)) \Rightarrow (r_1(i) > r_1(j)).$$

Quite aside from measurement theory considerations, the paradigm that we have described contains some important and not always obvious assumptions about behavior. These have been discussed in detail by Navon and Gopher (1979), so we shall mention them only briefly. One of the most important assumptions, and one of the hardest to justify, is that the performer is indeed operating at the point at which Task 1 performance shifts from a resource to a data limitation. Experimenters attempt to ensure this by instructing performers to devote enough effort to the primary task to perform it correctly, and to devote their remaining effort to the secondary task. In some experiments these instructions are supplemented by an explicit payoff scheme, so that a person who wishes to maximize objective rewards will perform at the data limiting point. Obviously a performer can do this only if the performer and the experimenter agree, quite precisely, on the meaning of the instructions and the values of the payoffs. Secondary task instructions also implicitly assume that the performer has a sophisticated knowledge of his/her personal performance-resource function for the task.

A second question concerns the concept of a general resource. Should we think of mental resources as commodities that are infinitely transferable from one task to another, like money, or as commodities that are very useful for some tasks and acceptable but less useful for others, like alternative sources of energy?

These issues are serious ones, and should not be minimized. Initially, however, we shall ignore them. We shall later examine the plausibility of the assumptions and consider how our data and models might be affected by their violation.

We shall be concerned with a third issue that has been raised as a problem for resource competition theories. In many of the nomothetic experiments that have been conducted, data has been aggregated over individuals. This often amounts to an assumption that there is negligible inter-individual variation in resource capacity, a highly questionable assumption. Rather than regarding inter-individual differences in capacity as a problem for experimental interpretation, we shall attempt to incorporate them within a resource competition model.

The Easy to Hard Paradigm

Much of our work is based on an experimental design that we have come to call the easy to hard paradigm. Imagine that two individuals are performing an easy version of Task 1, e.g., solving easy reasoning problems. It could easily happen that two individuals who perform at the same level (virtually perfectly) on this task might differ markedly in their ability to perform a more difficult reasoning task. The easy task would not be challenging enough to reveal the difference between the two performers. However, one might be able to discriminate between the two individuals by using the secondary task technique explained in the previous section. The "spare capacity" of each individual would be measured during performance of the easy version of Task 1. This spare capacity measure would predict performance on a more difficult version of Task 1.

This logic can be illustrated graphically by considering the POCs for two different individuals, A and B. The performance resource functions are shown in Figure 5 separately for performance on easy and hard versions of Task 1. In the easy condition (Figure 5a), both individuals are able to reach a high level of performance, and thus the easy task fails to discriminate between them. Individual differences do appear in the hard condition

(Figure 5b), where neither individual can reach maximum possible performance.

Insert Figure 5 about here

Now suppose that we wished to predict performance in the hard condition on the basis of performance in the easy condition. This would clearly be impossible since both individuals are performing at the same level (p^*), although they may be expending different amounts of resources to achieve this level of performance. However, we can use performance on a secondary task to predict performance on the hard version of Task 1. Although we cannot discriminate between persons A and B on the basis of unobservable performance-resource functions, we can discriminate between them on the basis of their POCs, which can be observed directly. Good performance on the secondary task should be an indication of spare capacity that could be usefully applied if the primary task became harder.

This is illustrated by the POCs shown in Figure 6. Both A and B perform the easy version of Task 1 at level p^* . However, A can achieve this performance with a smaller output of resources. Therefore, A will achieve a higher level of performance on Task 2 than B.

Insert Figure 6 about here

We have offered this informal presentation of the easy to hard paradigm to illustrate its intuitive appeal. A closer look at the reasoning behind the paradigm reveals additional complexities. Individuals can differ in several characteristics that are relevant to dual-task performance: a) structural parameters pertaining to performance of Task 1, which determine the resources necessary to perform that task at a given level; b) structural

parameters pertaining to performance on Task 2, which determine the resources necessary to perform that task at a given level; and c) total resource capacity. It is very difficult to analyze the contribution of each of these factors to performance in the dual-task situation by appealing to the type of intuitive argument so far presented. For this reason, a more formal, mathematical analysis is presented in the following section.

A Formal Model of Individual DifferencesDefinitions and Preliminary Notation

The model to be developed deals with the relations between primary and secondary task performance over four different conditions. Conditions will be indexed by the variable c , where

$c=0$; The secondary task is done alone

$c=1$; The primary task is done alone, at an easy level of difficulty

$c=1+$; The primary task is done at the easy level of difficulty, and the secondary task is performed concurrently

$c=2$; The primary task is done alone, at a hard level of difficulty

As an example, suppose that the primary task was to memorize either three or seven digits and that the secondary task was to respond to a visual signal. Condition $c=0$ would be a "probe alone" condition, in which the visual signal was presented and reaction time recorded. Condition $c=1$ would require memorizing three digits. Condition $c=1+$ would require memorizing three digits, and a visual probe signal might be presented during the rehearsal period. Condition $c=2$ would involve memorizing seven digits. Clearly condition $2+$ is a logical possibility, but it will not be dealt with here.

An individual performer, i ($i = 1 \dots N$), will be characterized by a triplet, (e_{1i}, e_{2i}, R_i) , where e_{1i} represents the i th individual's structural efficiency at the primary task, and e_{2i} represents the individual's structural efficiency at the secondary task. R_i represents the person's attentional resource limit, or capacity. Collectively, the individuals in an experiment constitute a set S , where

$$(9) \quad S = \{ (e_{1i}, e_{2i}, R_i) \} \quad i = 1 \dots N$$

Performance on any task t ($t = 1, 2$) requires the allocation of attentional resources to the task. Let $r_{ti}(c)$ be the amount of resources devoted to task t by individual i in condition c . By the definition of resource capacity,

$$(10) \quad 0 \leq r_{ti}(c) \leq R_i, \quad t = 1, 2 \quad i = 1 \dots N.$$

Let $p_{ti}(c)$ be the observed performance of person i on task t in condition c . Then

$$(11) \quad p_{ti}(c) = \text{Min} (f_t(r_{ti}(c); e_{ti}, d), D_t(e_{ti}, d))$$

where $f_t(r_{ti}(c); e_{ti}, d)$ is the performance-resource function for an individual with task structural parameter e_{ti} , who is faced with an external task of difficulty d ($d=1$, easy, $d=2$, hard), and $D_t(e_{ti}, d)$ is the data-limit function. This function establishes maximum performance for an individual, given the structural parameter and the external level of difficulty of the task.

It follows from (11) that there will be a "maximum economic investment" that a person should make in task t at a given level of difficulty and in a particular condition. Let this be $r_{ti}^*(c)$, where $r_{ti}^*(c)$ is the minimum value of $r_{ti}(c)$ that satisfies

$$(12) \quad f_t(r_{ti}^*(c); e_{ti}, d) = D_t(e_{ti}, d).$$

A person will be said to be an economic performer in condition c if and only if resources $r_{ti}^*(c)$ are invested in the primary task.

The assumption that f_t does not change over individuals and conditions, except for changes in parameters, is actually an assumption of some content. This sort of assumption is made in much psychological research. For instance, it is made in stronger form in virtually all research on learning, where individual parameters are fit to a generalized learning curve,

and in psychometrics, where the factorial content of a task is assumed not to change over individuals. It might be questioned in situations in which individuals could differ in the strategy with which they approach the task.

A point that will be important in later analyses is that $r_{ti}^*(c)$ is established within a condition by the value of e_{ti} . This is apparent from equation (11).

Task Assumptions

These assumptions deal with the resource requirements of the primary task at the easy ($d=1$) and hard ($d=2$) levels of difficulty, and with the requirements of the secondary task at its constant level of difficulty, $d=k$.

A.1 All individuals reach a data limiting point in performance of the easy primary task.

A.2 All individuals are resource-limited in performance of the hard primary task.

Comment: One of the primary tasks that we have used in our experiments provides an illustration of these assumptions. The task required active rehearsal of either a small or large number of letter-digit pairs. When there are only a few pairs to be rehearsed, subjects report that the task can be done with less than maximum output of effort, and most perform at a very high level. However, perfect performance is usually not attained due to momentary lapses or failure to correctly code a stimulus when it is presented. If there are many pairs to be rehearsed, it is difficult to reach the last pair to be rehearsed before the first pair is forgotten, and the effectiveness of rehearsal is closely tied to the effort put into the task.

A.3 All individuals reach a data limiting point in performance of the secondary task done alone.

A.4 All individuals are resource-limited in performance of the secondary task done in conjunction with the primary task.

Comment: A.3 states that if a person is able to devote all attentional resources to the secondary task, a point will be reached at which structural limitations determine performance. In our work secondary task performance generally required a simple motor response to a visual or auditory probe. At a certain point the reaction time (RT) to such a signal will be determined by equipment and structural, rather than resource, variables. A.3 asserts that people reached this point.

A.4 can be evaluated by inspecting the data. As the secondary task does not change its difficulty level, any difference in performance of an individual in the 0 and 1+ conditions will have to be associated with a change in resource allocation. If performance deteriorates from the 0 to 1+ condition then, perforce, performance in the 1+ condition must have been resource limited. This situation always arises in the experiments that we have completed on dual task performance.

A.5 Whenever any two tasks are done concurrently, some amount of attentional resources, Δ , will be diverted to the super ordinate task of coordinating the two concurrent tasks.

Comment: Assumption A.5 has been introduced to cope with the common observation that in a wide range of dual task studies primary task performance is worse in dual than single task conditions, in spite of instructions that primary task performance should be maintained (Kerr, 1973). Assumption A.5 amounts to an assertion that individuals set aside an economically appropriate amount of resources, r_{t1}^* (c), for primary task performance, but that this allocation is pre-empted by the automatically high priority assigned to

inter-task co-ordination. Note that Δ is not subscripted, indicating that individual differences in inter-task co-ordination will not be considered.

These assumptions lead to the following performance-resource functions:

- (13) $p_{1i}(1) = f_1(r_{1i}^*(1), e_{1i}, 1)$ Primary task, alone,
easy condition
- (14) $p_{1i}(1+) = f_1((r_{1i}^*(1) - \Delta), e_{1i}, 1)$ Primary task, dual,
easy condition
- (15) $p_{1i}(2) = f_1(R_i, e_{1i}, 2)$ Primary task, alone,
hard condition
- (17) $p_{2i}(0) = f_2(r_{2i}^*(0), e_{2i}, 2)$ Secondary task alone
- (18) $p_{2i}(1+) = f_2((R_i - r_{1i}^*(1)), e_{2i}, k)$ Secondary task, dual,
with easy primary task.

By virtue of the assumptions concerning data limitations (A.1 and A.3)

$$(19) \quad p_{1i}(1) = D_1(e_{1i}, 1)$$

and

$$(20) \quad p_{2i}(0) = D_2(e_{2i}, k).$$

On occasion we shall refer to a variable itself, rather than to a specific value of the variable. In such cases we write $p_t(c)$, suppressing the subscript for the individual. To refer to a set of observations for a particular task and condition we write

$$(21) \quad P_t(c) = \{ p_{ti}(c) \} \quad \begin{array}{l} t = 1, 2 \\ i = 1 \dots N \\ c = 0, 1, 1+, 2. \end{array}$$

An analogous notation will be used to refer to structural and resource variables, e_1 , e_2 , and R .

Assumptions about unobservables

The variables e_1 , e_2 , and R play a role analogous to the role of latent traits in psychometric theories of intelligence. They are in principle unobservable, but they are presumed to establish the observable values. In this section some assumptions will be made about the relationship between the unobservable variables. In the following section these will be combined with the assumptions about the unobservable-observable relations expressed in equations (13) through (18), in order to derive predictions about the relations between observables. This procedure resembles the data handling techniques used in the analysis of causal models (Bentler, 1980). The mathematics are different because we limit our assumptions about observable-unobservable relations to the concept of a performance-resource function and because we allow for the possibility of non-linear relations. Therefore we shall base our analysis upon information-theoretic concepts rather than upon the partitioning of covariances into components.

Summary comments on information theory

This subsection presents some information-theoretic concepts that will be used in this paper. The presentation is intended to be a reminder of such concepts rather than a tutorial discussion. (Luce (1960) provides an excellent presentation in depth.) The notation stands apart from that in the rest of the paper.

Imagine two abstract variables, x and y , with associated sets of probabilities

$$(22) \quad \underline{X} = \{ \underline{p} (x=a) \} \quad a \in \text{range of } x$$

$$\underline{Y} = \{ \underline{p} (y=b) \} \quad b \in \text{range of } y.$$

The information in each of these variables is defined as

$$(23) \quad H(x) = - \sum_a \underline{p} (x=a) \log_2 (\underline{p} (x=a))$$

and similarly for $H(y)$. The set of probabilities

$$(24) \quad \underline{X} \times \underline{Y} = \{ \underline{p} (x=a \& y=b) \}$$

states the probabilities of pairs of values for x and y , and

$$(25) \quad H(x,y) = - \sum_a \sum_b \underline{p} (x=a, y=b) \log_2 (\underline{p} (x=a, y=b)).$$

Equation (24) can be used to define the sets of conditional probabilities $p(x=a : y=b)$ and $p(y=b : x=a)$, with the associated information measures $H(x : y=b)$ and $H(y : x=a)$. The average information in y , given x , is defined by

$$(26) \quad H(y:x) = \sum_a \underline{p}(x=a) H(y:x=a) .$$

The information in a pair of observations can be expressed in terms of the information in the individual observations and the conditional probabilities, as

$$(27) \quad H(x,y) = H(x) + H(y:x)$$

$$= H(y) + H(x:y).$$

The maximum value of $H(x,y)$ is

$$(28) \quad H_{\max} (x,y) = H(x) + H(y)$$

which is reached only when

$$(29) \quad H(y:x) = H(y) \quad \text{and} \quad H(x:y) = H(x) \quad .$$

This is sometimes stated in terms of the information transmitted from x to y , which is defined by

$$\begin{aligned} (30) \quad T(x;y) &= H_{\max}(x,y) - H(x,y) \\ &= H(x) - H(x:y) \\ &= H(y) - H(y:x). \end{aligned}$$

Two variables are said to be independent if $T(x;y)$ is zero. Note that this is a more general definition of independence than the statement that there is a zero product-moment correlation between x and y , as $T(x;y)$ encompasses any functional relationship at all. Thus if $T(x;y)$ is zero there is no way of predicting the value of x from y .

Even when $T(x;y)$ is greater than zero, prediction is not always symmetric, as the following example shows. Suppose that variable x may take the values $-1, 1, -2, 2$ with equal probability, and that $y = x^2$. It is easy to show that in this case

$$\begin{aligned} (32) \quad H(x) &= 2 \\ H(y) &= 1 \\ H(x,y) &= 2. \end{aligned}$$

In terms of conditional information

$$\begin{aligned} (33) \quad T(x;y) &= 1 \\ H(x:y) &= 1 \\ H(y:x) &= 0. \end{aligned}$$

Thus y is perfectly predictable from x , but not vice versa. This situation can be expected to arise in observable-unobservable relationships. The

observable should be predictable given the values of an individual's parameters, but two or more combinations of parameters might give rise to the same observation.

Now consider the case of three variables, x , y , and z , with the associated probability distributions. If $H(x,y,z)$ is the information in the set of triplets, $\{ (x,y,z) \}$, then the information transmitted from the (x,y) pair to the z pair, or vice versa, is

$$(34) \quad T(x,y,z) = H(x,y) + H(z) - H(x,y,z).$$

The conditional information transmitted from x to z , or from z to x , after allowing for the information transmitted by y is

$$(35) \quad T(x,z: y) = H(x,y) + H(y,z) - H(y) - H(x,y,z).$$

The expressions for $T(y,z:x)$ and $T(x,y:z)$ are similar.

There is a particular meaning of $T(x,y)$ that should be kept in mind. If the transmitted information between a pair of variables is greater than zero, then it is possible to use knowledge of one variable to make a good estimate of the other, provided that "good estimate" is defined in terms of the probability distributions. To use an illustration that will be important later, suppose we define a best estimate as one that minimizes the conventional least squares loss function,

$$(36) \quad L = \sum_y p(y)(y - \tilde{y})^2$$

where \tilde{y} is the estimate of y . If $T(x,y) > 0$, then there is some function $g(x)$ such that

$$(37) \quad \tilde{y} = g(x)$$

will, on the average, produce a lower value of L than simply using the expectation of y , $(E(y))$, as the estimate of y .

Individual parameters and their relations

We may think of all conceivable values of the parameter variables, e_1 , e_2 , and R , as having certain a priori probabilities of occurrence, both individually ($p(e_{1i}=a)$, etc.) and in pairs ($p(e_{1i}=a, e_{2i}=b)$) and triplets. Our basic assumption is that, in the information-theoretic sense,

A.6 An individual's attentional resource capacity is independent of the individual's structural parameters.

This can be stated formally as

$$(38) \quad T(R; e_1) = T(R; e_2) = 0.$$

This assumption effectively defines resources as those capacities of the individual that are relevant to performance but independent of the ability to do any one task. Such a definition is at first reminiscent of g , the general ability in classic intelligence theory. At the empirical level there is a slight difference in definitions, since resource capacity could be identified by non-linear relationships between performance over different tasks, while g , as strictly defined in factor analytic studies, is determined by linear relations. We suspect that most intelligence theorists would regard this as a minor technological quibble, and we agree. A more basic difference is the requirement that resource capacity be shared over all concurrent tasks (equation (10)). We know of no proposal that g is something that the individual must parcel out over different ongoing activities. There seems to us to be no way of distinguishing between the ideas of general attentional resources and general intellectual competence so long as

one deals only with statistical relationships between performance on different tasks done one at a time. The distinction between the two concepts depends upon performance when tasks can compete for attention.

Constraints on the relationships between observables

We are now in a position to state constraints on the relations between observables. Such constraints, of course, provide the basis for empirical testing of the model. The constraints will be stated by designating performance on the primary task alone, at the hard level of difficulty (variable $p_1(2)$) as a target variable, and expressing this variable in terms of the other observable variables. Our approach will be to regard performance-resource functions as mappings between sets of observable and unobservable variables. We then examine the information-theoretic consequences of these mappings. To aid in following the argument, Table 1 summarizes the mappings involved. The same information is shown graphically in Figure 7

Insert Table 1 About here

which depicts the unobservable variables e_1 , e_2 , and R , as being connected to the observable variables by arrows, whose direction is intended to illustrate causation. Unobservable variables e_1 and e_2 are connected to each other by a double-headed arrow, indicating that the model permits a statistical association between these variables without any implication of causation. Variable R stands alone since, by assumption, it is independent of the structural variables.

Insert Figure 7 about here

How should we go about predicting target variable performance from knowledge of the other variables? We shall first present an informal argument, which may be followed graphically by examining Figure 7. It is clear from this figure that target variable performance, $p_1(2)$, depends jointly upon e_1 and R . Thus any information that improves our ability to predict e_1 and R should improve our prediction of target variable performance. What are the sources of information that we can use to estimate the two unobservables?

Our basic approach is to work backward from observables. Suppose, for the moment, that we knew the performance-resource functions and that we could state a priori probabilities for all values of the unobservables. In general, a performance-resource function will establish a many:one mapping from the set of possible values of unobservable parameter into the set of possible values of an observable performance. Thus if we determine the performance of a particular individual in a given situation, we should improve our estimate of that individual's parameters, and this, in turn, should make it possible for us to predict performance in a new situation, providing that the new performance depends (partly) upon the same unobservable parameters. However, there may be redundancies between the predictor variables. By this, we mean that there may be two or more performance measures that yield the same, or nearly the same, information about unobservables. With these considerations in mind, let us examine ways to predict target variable performance.

Performance on the easy version of the primary task (variables $p_1(1)$ and $p_1(1+)$) depends upon the primary task structural parameter, e_1 . This is an example of the general rule that if performance is data-limited, then there is a mapping from the structural parameter for that task into performance. Thus information about e_1 can be obtained by examining $p_1(1)$ and $p_1(1+)$.

Whether or not these two information sources are redundant depends upon the value of Δ , the amount of resources devoted to co-ordination between tasks in a dual task condition. If Δ is zero then $p_1(1)$ and $p_1(1+)$ are completely redundant.

Information about e_1 may also be obtained by examining secondary task performance either alone or in the dual task condition ($p_2(0)$ and $p_2(1+)$). Consider first the case of secondary task performance alone, variable $p_2(0)$. Since this performance is data-limited, there will be a mapping onto performance from the set of possible e_2 values, making it possible to improve our estimate of the secondary task structural parameter. If there is a statistical (not causal) association between the two structural parameters this relationship can be used to estimate the value of e_1 . The logic is similar to the logic of using a measure of arm strength to estimate leg strength; there is no direct causal connection between the two measures, but knowledge of one would probably improve prediction of the other.

The case of secondary task performance in the dual task condition, variable $p_2(1+)$, is more complicated. Variable e_1 can be estimated indirectly, through estimation of e_2 , as described above. Variable $p_2(1+)$, however, is a resource-limited variable. The amount of resources made available to the secondary task in the dual task condition will be equal to the difference between the individual's resource capacity and the resources required to bring the primary task to its data limit (R_i and $r_{1i}^*(1+)$). The latter variable is determined by e_{1i} , the individual's primary task structural parameter. Thus secondary task performance in the dual task condition will be partly dependent upon the primary task structural parameter.

Finally, how are we to estimate resource capacity, R . This enters into the determination of only two performance variables, the target variable itself

and secondary task performance in the dual task condition. Thus secondary task performance in the dual task condition is connected to target variable performance by three chains of information, links through e_1 and e_2 , which may be partly or wholly redundant to the links connecting target variable performance to other predictors, and by a link through R , which is independent of the chains of information involving other predictor variables.

Turning again to Figure 7, each of these links correspond to paths in the graph. There are paths from $p_1(1)$, $p_1(1+)$, and $p_2(1+)$ to $p_1(2)$ going through e_1 . There are paths that go from $p_2(0)$ and $p_2(1+)$ to $p_1(2)$ by moving first to e_2 and then to e_1 . Only $p_2(1+)$ has a path that moves to $p_1(2)$ through R .

The information-theoretic basis for the assertions will now be given.

The performance-resource function states that the value of $p_1(2)$ is completely established (within the limits of measurement error) when the pair of parameters (e_1, R) is known. Furthermore, by the definition of a performance-resource function, any change in R will cause a change in performance, since hard primary performance is resource limited. The information transmitted from R to $p_1(2)$, independently of e_1 , is

$$(39) \quad T(R, p_1(2): e_1) = H(e_1, R) + H(e_1, p_1(2)) - H(e_1) - H(e_1, R, p_1(2)).$$

Because $p_1(2)$ is completely determined by e_1 and R ,

$$(40) \quad H(e_1, R, p_1(2)) = H(e_1, R).$$

Substituting (40) into (39),

$$(41) \quad \begin{aligned} T(R, p_1(2): e_1) &= H(e_1, p_1(2)) - H(e_1) \\ &= H(p_1(2): e_1) \\ &= \sum_a p(e_1=a) H(p_1(2): e_1=a). \end{aligned}$$

By the definition of resource limited, and the performance-resource function it is true that for every pair of values $R_i, R_i', R_i \neq R_i'$,

$$(42) \quad f_1(R_i; e_{1i}, 2) \neq f_1(R_i'; e_{1i}', 2)$$

if $e_{1i} = e_{1i}'$.

Thus for fixed e_1 , there is a one: one mapping from R to $p_1(2)$. This means that

$$(43) \quad H(p_1(2) : e_1=a) = H(R : e_1=a).$$

By assumption on A.6, e_1 and R are independent. Therefore

$$(44) \quad H(R : e_1 = a) = H(R)$$

and therefore

$$(45) \quad T(R, p_1(2); e_1) = H(R).$$

Equation (45) states that unless R is known completely there will be uncertainty in predicting the target variable, regardless of how accurately we have established the value of the structural parameter e_1 . Thus it always pays to improve prediction of R , since this always reduces the uncertainty in estimating the target variable.

The situation is not quite the same with respect to e_1 . By reasoning similar to the derivation of (41),

$$(46) \quad \begin{aligned} T(e_1, p_1(2); R) &= H(p_1(2) : R) \\ &= \sum_b p(R=b) H(p_1(2) : R=b) \end{aligned}$$

However the performance-resource function does not define any condition for fixed R and varying e_1 . In fact, quite reasonable functions can be drawn

that show $e_{1i} \neq e_{1i'}$, but for some R

$$(47) \quad f_1(R=b; e_{1i}, 2) = f_1(R=b; e_{1i'}, 2).$$

An example is illustrated in Figure 8. The only restriction is that if the

Insert Figure 8 about here

e_1 's are not equal there be some value of the pair (R, e_1) for which (47) is false. In the figure, three performance-resource functions are shown, for $e_1 = a, b, c$. Given that e_1 is known, it is still necessary to establish R before an estimate of $p_1(2)$ can be made. However, if R is known one would not need to discriminate between $e_1=a$ and $e_1=b$ in order to estimate target performance.

This reasoning is illustrated formally by observing that

$$(48) \quad H(p_1(2):R) \leq H(e_1)$$

and therefore

$$(49) \quad 0 \leq T(e_1, p_1(2) : R) \leq H(e_1).$$

This means that whether or not improving one's estimate of e_1 improves prediction of $p_1(2)$ depends on exactly how the estimation is made. If the reduction in information obtained through the estimation procedure is greater than $H(e_1) - T(e_1, p_1(2) : R)$, then improvement is bound to occur. If the reduction is not this great, then whether or not prediction is improved depends on whether or not the prediction allows one to discriminate between possible values of e_1 for which (47) is not satisfied. This can be seen by examining Figure 8. Suppose that it has been established that $R_1 = R^*$. Any

information that alters the probability that $e_{1i} = c$ will transmit information about the value of the target variable. Information that changes $p(e_{1i}=a)$ and $p(e_{1i}=b)$ relative to each other, but leaves unchanged the probability that the value is either a or b, will not influence the accuracy of a prediction.

The results established for $p_1(2)$ generalize to the prediction of performance in any resource-limited situation. Since information transmission is defined by a statistical relationship rather than by an interpretation of causality, prediction is possible in both directions. This may also be seen by examining Figure 8. If performance were to be observed at point p^* , then resource capacity would have to be either at point R^* or R^{**} . The results also apply to residual uncertainties. That is, suppose that by utilizing one set of observations we obtained an imperfect estimate of the e_t 's and the R value. We could apply the reasoning given above to an analysis of residual variation in the unobservables, after allowance had been made for the reduction in uncertainty due to the initial observations.

A stepwise technique for predicting hard primary task performance will now be developed. It is clear from Figure 7 and from the mappings stated in Table 1 that statistical associations between the two primary task measures ($p_1(1)$ and $p_1(2)$) will be due to their joint dependence on e_1 , the primary task structure variable. The performance-resource function establishes a many:one mapping from $E_1(1)$ to $P_1(1)$, hence

$$\begin{aligned} (50) \quad T(e_1, p_1(1)) &= H(p_1(1)) + H(e_1) - H(p_1, e_1) \\ &= H(p_1(1)) + H(e_1) - (H(e_1) + H(p_1(1):e_1)) . \end{aligned}$$

Since $H(p_1(1):e_1) = 0$, from the definition of a data limit, (50) reduces to

$$(51) \quad T(e_1, p_1(1)) = H(p_1(1)).$$

Thus if there is any variation in the observable, primary task performance in the easy-alone condition, this variation can be used to gain some information about the primary task structural parameter, e_1 . Whether or not this information will aid in determining primary task performance in the hard-alone condition depends on the considerations given in discussing equations (48) and (49). Information about e_1 may help in prediction, and our intuitions are that it usually will, but within the restrictions established by the model, we can construct a situation in which this is not true.

A similar argument applies to the prediction of hard primary task alone performance from performance on the secondary task alone, variable $p_2(0)$. The only additional comment is that the prediction involves two steps. Given observed performance, the secondary task structural parameter, e_2 , can be estimated. If $T(e_1, e_2)$ is not zero (and the assumptions of the model permit either condition), then prediction of e_1 is possible, indirectly, through e_2 . Again our intuitions are that such information will assist in predicting the target variable, but the model does not demand that this be so.

Much stronger restrictions apply when we consider the variable $p_2(1+)$, secondary task performance in the dual task condition. From Table 1, we see that $p_2(1+)$ is a function of e_2 , $r_1^*(1+)$, and R . The variable $r_1^*(1+)$, however, is itself a function of e_1 . Thus the performance-resource function for the secondary task in the dual condition can be written

$$(52) \quad p_2(1+) = f_2^* (R; \underline{e})$$

where

$$(53) \quad \underline{e} = (e_1, e_2).$$

By the argument presented for $p_1(2)$, we can express the information shared by the observable, $p_2(1+)$, and the resource capacity variable, R , as

$$(54) \quad T(p_2(1+), R; \underline{e}) = H(R),$$

and this is independent of information associated with \underline{e} . This does not mean that R is perfectly predictable from knowledge of secondary task performance in the dual task condition, but it does mean that by observing this performance one can improve one's guess concerning the value of R . See the analogous illustration associated with Figure 8. As improving one's prediction of R will always help in predicting the target variable, the model demands that there be an association between $p_1(2)$ and $p_2(1+)$. Furthermore, at least part of this association should be independent of any association due to joint statistical relations between these variables and any of the other observables.

The information-theoretic analysis can be summarized in a form that approximates conventional statistical analysis. Two variables will be said to be associated if there is a statistically reliable correlation between the first variable, y , and a prediction function, $\tilde{y} = g(x)$ of the second variable. The arguments presented above show that there "may exist" two functions, $g_1(p_1(1))$ and $g_2(p_2(0))$ that associate the target variable, primary task performance in the hard-alone condition, with primary task performance in the easy-alone condition and secondary task performance in the secondary task alone condition. There must exist a function $g_0(p_2(1+))$ that associates secondary task performance in the dual task condition with the target variable. Furthermore, this association is at least partially independent of the two previous associations if they do exist.

Suppose that we knew what the prediction functions g_0 , g_1 , and g_2 were.

We could then construct y_0 , y_1 , and y_2 and test the model's predictions, by examining the first order and partial correlations between the y 's and the target variable. In the following subsection a method of estimating the prediction functions is presented.

Approximation by linear polynomials

There is no way to identify the g 's in the preceding analysis without providing a task-specific model of response production. In order to test the general resource competition model, though, we do not need to know what the g functions are. All we need to know is what they can predict. This can be done if we find an arbitrary (and not psychologically interpretable) approximation to each g function. Our approach makes use of the fact that if x and y are arbitrary real variables, and y is a single valued function $y=g(x)$ of x , then g may be approximated by the linear polynomial function

$$(55) \quad \tilde{g}(x) = \sum_{v=0}^K a_v x^v$$

for some unknown K . In practice, if we are given N data points, (x_i, y_i) , and if $(x_i = x_j)$ implies that $(y_i = y_j)$, then the relation between x and y in this data set can be stated exactly by (55), with $K \leq N-1$. (If the equality condition is not met, we can reformulate the problem by replacing the various y 's at a given x value by their average. Fluctuation about this point is thus assumed to be due to variation in y not associated with x .)

In practice, we would not want to calculate (55) for K as high as $N-1$, as this would maximally capitalize on chance fluctuations in the data. Instead we can set limits on the value of K . One limit is simply intuition: we find it hard to imagine reasonable psychological functions that would require approximations using terms higher than $K=5$. In practice we have used 6 and 10 as limits on K . (See Tukey (1977) for a discussion of the

introduction of such arbitrary assumptions.) A second limit is established by the reliability of the data. If we know that the reliability of the predictor is only \underline{r} , there is little point in choosing K to be so large that the correlation between y and $g(x)$ exceeds \underline{r} .

In practice, we have used the following technique. Given two observables, x and y , with y to be predicted using a possibly non-linear function of x , we calculate the multiple regression of y on the variables $x_v = x^v$, for $v = 1..K$, where K is either an arbitrarily established limit, or the value of v at which the multiple regression first exceeds the reliability imposed by the data. Predictor variables are entered in order of ascending v 's. We then examine the resulting regression equation, and set to zero any regression weight a_v which is not reliably different from zero. The .01 criterion of reliability has been adopted, but we do not follow it "slavishly", i.e. if a significance level of .02 or .03 is noticed we experiment with regression equations that do or do not use the variable. We then calculate the multiple regression using only the reliable variables, and determine whether or not there is any change in the multiple regression. If there is no large change, the process terminates, and the resulting g is our approximation of g . If there is a change, we then experiment with various combinations of predictor variables to determine whether or not we have uncovered a suppressor variable. (We did uncover one case of "classical suppression" in one of our analyses. The mathematical basis is described by Cohen and Cohen (1975, pg. 87).) If suppressor variables are discovered they are included in the equation.

The linear polynomial approximation procedure may involve substantial capitalization on chance fluctuations in the data. Therefore we recommend it only for large studies. In practice we shall apply it to a study involving 81 subjects. To deal with smaller studies we apply the much more arbitrary criterion of dealing only with linear relations (i.e. $K=1$), and

using conventional correlational analyses. The resource competition model provides some justification for doing so whenever we are dealing with a relation between observables that is dependent on resource capacity, the R variable. By the definition of a performance-resource function, performance will always be an increasing function of R in resource-limited situations, hence there should always be a positive linear term in the function relating two observables to R . If the relationship between observables is traced through one of the structure parameters, e_1 or e_2 , a linear analysis introduces an additional assumption. This is that the task structural parameter is unidimensional, and that there is the same ordinal relationship between the structural variable and both the observable performance variables. While this assumption does not seem to be unreasonable (and is not required in the non-linear analysis) we do want to be aware that we are making it.

The use of a linear analysis is perhaps least justified when we examine the independence of predictions of the target variable based on different predictors. Suppose we find that there is some predictability in the y variable associated with a linear function of x (as in conventional correlational analysis) and that there is a further component of y that can be predicted by a linear analysis using a second predictor, z . It is possible that the additional component, which appears to be predictable only from z , might be predictable by a non-linear association between x and y . While this may seem to be an unlikely possibility in practice, we do want to be aware that there is nothing in either the resource competition model or in the mathematics of approximation that guards against such a spurious result.

In summary, the technique of approximation of predictor functions by linear polynomial analysis provides a justifiable way of examining the implications of the resource competition model. The approximation

technique, however, requires precise data that can be obtained only in a large experiment. Conventional linear analysis can be justified in some cases, but may suppress relationships that could cause us to question the model. In practice what we have done is to apply a linear analysis to smaller experiments, and a non-linear analysis to very similar larger studies. We then ask whether or not the approximation functions uncovered by the non-linear analysis raise questions about the interpretation of the linear analysis.

Experimental Results

The resource competition model has been used to analyze several experiments in a series of studies of dual task performance (Lansman and Hunt, Note 1). All of the experiments used the "easy to hard" paradigm, in which performance on a difficult primary task, done alone, was predicted from various combinations of primary and secondary task performance. A linear analysis of two smaller experiments, involving about 50 subjects each, will be reported first, and then a non-linear analysis of a larger study, involving 81 subjects.

The first two experiments used a verbal short-term memory task as the primary task. The sequence of events observed by the subject is shown in Table 2. First several letter-digit pairs were presented, to establish an initial set of paired associates to be retained in memory. Each subsequent trial contained a test phase and a study phase. During the test phase, a letter would be presented with a question mark, and the subject would attempt to recall the digit most recently paired with that letter. In the study phase, the same letter would be presented, paired with a new digit. The difficulty of this task was manipulated by varying the number of letter-digit pairs involved.

Table 2 about here

This task is generally referred to as a continuous paired associates task. The present form was developed by Atkinson and Shiffrin (1968), who used it to test their buffer model of short-term memory. A similar task was used by Yntema and Meuser (1962) some years earlier. Performance on the task has been shown to be related to scores on tests of

scholastic aptitude (Hunt, Frost, & Lunneborg, 1973) and to the performance of computer programmers (Love, 1977).

A probe reaction time task was used as a secondary task. In dual task conditions, a probe was presented during the study phase of 75% of the trials. In one experiment, the probe signal was a set of asterisks shown immediately above the letter-digit pair. In the other, the probe was a tone presented through headphones. Subjects responded to the asterisks by pressing a key, and to the tone by speaking the syllable "Bop" into a microphone. Paired associate and probe tasks never required a response during the same interval.

If resource competition is involved, the secondary and primary tasks should interfere with each other. Figure 9a shows performance on the paired associates task as a function of the number of pairs to be maintained in memory and the presence or absence of the probe task. Figure 9b shows probe reaction time (RT) as a function of the difficulty of the concurrent memory task. The zero memory load condition represents the probe task done alone. The pattern of interference between tasks is typical of that found in many experiments. Mutual interference is evident, and the greatest increment in probe reaction time is associated with the change from the probe alone condition to the probe plus memory task condition. Smaller increments in probe RT occur as the difficulty of the memory task increased.

Insert Figure 9 about here

If our model of individual differences is correct, then we would expect performance on easy and hard versions of the primary task to be correlated, since they are both influenced by e_1 , the structural parameter

for the primary task. Performance on the hard primary may also be predicted by RT in the secondary task done alone, due to a correlation between e_1 and e_2 . However, RT to the probe in the dual task condition should improve prediction of accuracy on the hard primary task, since RT in the dual task condition is influenced by resource capacity, R , as well as e_2 .

Table 3 summarizes the linear correlations obtained in the two experiments. Of greatest interest are the partial correlations between accuracy on the hard primary task (the target variable in our theoretical analysis) and probe RT in the dual task condition. The variable "held constant" by the partial correlation technique is either accuracy in the easy primary task done alone or probe RT in the secondary task done alone, or both of these. The partial correlations are shown in the three right-most columns of the table. In each case the correlation is reliably different from zero. Thus probe RT in the dual task condition was significantly correlated with the target variable, even after the two single task variables were statistically removed.

Insert Table 3 about here

A third experiment involved 81 subjects, selected from a wide adult age range in order to maximize individual differences. The first part of this experiment was essentially a replication of the previous work. The primary task was the continuous paired associates task, and the secondary task involved manual response to an auditory probe. The second part of the experiment involved a new primary task. Subjects were shown a random pattern of plus (+) signs on a computer display screen. This standard pattern was followed by a mask, and then by a

pattern of plus signs that was either identical to the standard or differed from it by the movement of a single plus. The subject's task was to indicate whether the second pattern was identical to or different from the standard. In the easy version of this task, patterns were composed of four plus signs in a 3 x 3 matrix. In the hard version, there were ten plus signs in a 7 x 7 matrix. As in the case of the paired associates task, probes were presented during the study phase of 75% of the trials. The exact sequence of events is shown in Figure 10.

Insert Figure 10 about here

Table 4 shows data from the paired associates task. Presented are correlations of the target variable, performance on the hard paired associates task, with linear and non-linear functions of several predictor variables. Of particular interest is the correlation between the target variable and performance on the secondary task in the dual condition, after the effects of the other two predictors have been held constant by partial correlation. This correlation is reliably greater than zero in both the linear and non-linear analyses.

- - - - -
Insert Table 4 about here
- - - - -

A glance at the table shows that there are only slight differences between the linear and non-linear analyses. These differences would not change our conclusions in any way. This result strengthens our confidence in the linear analyses of the smaller experiments. Visual inspection of the form of the non-linear analyses indicates that they all have strong linear components, and that the non-linearities are usually introduced

to modulate extreme effects, for example, to correct for excessively pessimistic prediction associated with extremely long RTs.

A rather different picture emerged from examination of the data from the spatial memory task. Two observations led us to suspect that even the difficult version of this task was not resource-limited. First, although the primary task did interfere with the secondary, the effect was much smaller than in the experiments using the paired associate primary task. Figure 11 compares the effects of the spatial memory and paired associate tasks on probe RT. The second observation was that subjects reported quite different strategies in attacking the two tasks. The paired associates task was almost always attacked by concentrated rehearsal of the current pairs. No such rehearsal strategy is available for the spatial memory task. Instead, subjects reported that a passive approach of simply looking at the standard patterns was most effective. If active rehearsal strategies are ineffective in the spatial memory task, then we would expect data rather than resource limitations to be important in determining performance on that task.

Table 5 presents the linear and non-linear correlations for the spatial memory task. Consider first the linear analyses. No reliable partial correlation remains between RT in the dual task condition and accuracy in the hard spatial memory task, after allowing for individual variability in single task conditions. The same thing is true in the non-linear analysis. Although the non-linear analysis is not identical to the linear analyses (because of the change in correlation between the target variable and performance in the probe alone condition) the partial correlations measuring the predictability of the target from secondary task performance in the dual condition remain low. In terms of the model, there does not seem to be a path leading to the target variable

via the resource latent variable (R). This situation would arise if performance were data limited throughout levels of difficulty of the spatial memory task.

CONCLUDING REMARKSAn evaluation of the approach

The idea that allocatable attentional resources must be considered in the analysis of cognition is an important one. Nevertheless, problems have arisen in the development of resource competition models that have posed serious difficulties for experimental psychologists. One of these problems is that individual differences in both resource capacity and specific task efficiency almost certainly exist. This prevents a straightforward interpretation of many experimental designs. A second problem in the analysis of resource competition studies is that individuals may not follow the particular resource allocation policy that the experimenter would like them to use. The third problem is that the notion of a mental resource is itself a vague one. Should we think of a single pool of infinitely transferable resources, or should we think of multiple resources with varying degrees of transferability? An even more basic question is, "What, precisely, are these resources supposed to be?" Should they be given a physiological interpretation or should we be content to deal with abstract concepts?

Our results are addressed directly to the first question. We believe that there are indeed individual differences in both resource capacity and specific task structure parameters, but we do not regard this fact as a reason for avoiding these concepts. Rather, they provide a topic for study. The problem of how individual differences enter into performance on multiple tasks is an involved one, and intuitions are not always adequate in drawing out the implications of formal models. Thus, we believe that study of the formal models is indeed necessary. In developing models one need not restrict oneself to the usual assumption

of linear measurement that underlies conventional correlational analysis. The approximation technique used here is a strictly empirical one, that allows us to trace through the steps in an information transmission model. Such an approach is satisfactory only as an interim step. The resulting linear polynomial expressions show what non-linearities exist, but do not provide an interpretable algebraic expression. It would be far preferable to unite models of individual differences with more precise models of how responses are produced in various tasks, so that we could examine the adequacy of specific, theoretically justifiable functions as explanations of the data.

Our own experimental work, and research in this area in general, is vulnerable to the second objection. Experimenters rarely know what resource allocation policies are being used by their subjects. Subjects are instructed to behave in an economically efficient manner, but do they listen? Indeed, even if they try to follow instructions, do they have that much control over resource allocation? In more analytic terms, we have assumed that our subjects located themselves at a particular point on the performance operating characteristic. There are techniques for checking this assumption, but they are time consuming, and are considered feasible in experiments that involve only a few participants. As individual differences designs usually require the study of large numbers of subjects, experiments that are "completely adequate" from both an individual differences and an attentional theory point of view are likely to be expensive. Unless designs are found to solve this problem, it may well be the limiting feature of the line of research.

This paper has not addressed the question of whether resources are unitary or multiple. Experimental designs that consider only a single pair of tasks cannot answer questions about the specificity of resources.

Obviously, we can only talk about competition for resources between the tasks that we observe. However, there is no reason why the methods used here could not be extended to the study of interference patterns observed between multiple pairs of tasks. It should be possible to develop models of resource competition for situations in which the same individuals attack different combinations of primary and secondary tasks. We could then ask whether one could describe the data by assuming a single resource capacity, or whether it was necessary to describe individuals in terms of several different resources. Such an analysis could be combined with nomothetic approaches, which stress the types of tasks that interfere with each other. The two approaches should lead to a common definition of resources.

The meaning of attentional resources

In this paper, the term "attentional resources" has been treated as an abstract concept to be defined by parameters in sets of equations. The physiological approach to attention assumes that the concept has some sort of corporeal reality. Two broad classes of explanation of "attention" have been offered. One is that attention means the application of some sort of processing unit within the brain, a unit that is required in the execution of a large number of tasks. An alternative is to regard attention as an energy concept, where the analogy is to the distribution of electric current or water pressure, rather than to time sharing of a piece of equipment. One could develop formal models that proceeded from either assumption. We expect, though, that it would be extremely difficult to distinguish between such models on the basis of conventional psychological experiments alone.

If formal models are to be used to address the question "What is attention?" it may be that they will be most helpful if the parameters

used to describe an individual's resource capacity are regarded as dependent variables to be predicted by non-psychological factors, such as age, state of alertness, drug state, or other measures of physical condition. Thus we would eventually define resource capacity in two ways: as a determiner of performance in psychological experiments, as we have done here, and as a measure that is responsive to certain types of variation in an individual's mental state. Does capacity change systematically with age? Is it responsive to training? Can capacity be altered by either natural or unnatural changes in physiological condition? Even if the approach developed here is successful in defining a mathematical model of attention, it will still be necessary to conduct experiments to define the concept of resource capacity in terms of the controlling independent variables. Such research must focus on dual tasks, rather than on the execution of one task at a time, because performance on a single task, done alone, does not allow one to distinguish between the efficiency with which a person executes a task and the amount of resources that the person devotes to it.

Footnote

1. This research was supported by the Office of Naval Research, Contract #N00014-77-0225, Earl Hunt, principal investigator. We would like to thank Colene McKee for assistance in the analyses reported here, and Christopher Hertzog for his assistance in discussing some of the statistical issues involved.

Reference Note

1. Lansman, M. & Hunt, E.B. Individual differences in dual task performance. University of Washington, Department of Psychology Technical Report, August, 1977.

References

- Atkinson, R.C., & Shiffrin, R.M. Human memory: A proposed system and its control processes. In K.W. Spence, & J.T. Spence (Eds.), The psychology of learning and motivation: Advances in research and theory (Vol. 2). New York: Academic Press, 1968.
- Baddeley, A.D., & Hitch, G. Working memory. In G.H. Bower (Ed.), The psychology of learning and motivation (Vol. 8). New York: Academic Press, 1974.
- Bentler, P.M. Multivariate analysis with latent variables: Causal modeling. Annual Review Psychology, 1980, 31, 419-456.
- Cohen, J., & Cohen, P. Applied multiple regressional correlation analysis for the behavioral sciences. Hillsdale, New Jersey: Erlbaum, 1975.
- Hunt, E., Frost, N., & Lunneborg, C. Individual differences in cognition: A new approach to intelligence. In G. Bower (Ed.), The psychology of learning and motivation (Vol. 7). New York: Academic Press, 1973.
- Hunt, E., Lunneborg, C., & Lewis, J. What does it mean to be high verbal? Cognitive Psychology, 1975, 7, 194-227.
- Hunt, E., & Poltrock, S. The mechanics of thought. In B. Kantowitz (Ed.), Human information processing: Tutorials in performance and cognition. Potomac, Maryland: Erlbaum, 1974.
- Kahneman, D. Attention and effort. Englewood Cliffs, New Jersey: Prentice-Hall, 1973.
- Kerr, B. Processing demands during mental operations. Memory and Cognition, 1973, 1, 401-412.
- Love, T. Relating individual differences in computer programming performance to human information processing abilities. Unpublished doctoral dissertation. University of Washington, 1977.

- Luce, R.D. Theory of selective information and some of its behavioral applications. In R.D. Luce (Ed.), Developments in mathematical psychology. Glencoe, Illinois: Free Press, 1960.
- Navan, D., & Gopher, D. On the economy of the human-processing system. Psychological Review, 1979, 86, 214-255.
- Norman, D.A. & Bobrow, D.B. On data-limited and resource-limited processes. Cognitive Psychology, 1975, 7, 44-64.
- Pellegrino, J.W., & Glaser, R. Editorial: Cognitive correlates and components in the analysis of individual differences. Intelligence, 1979, 3, 187-216.
- Posner, M.F. Chronometric explorations of mind. New York: Erlbaum, 1978.
- Simon, H. The science of the artificial. Cambridge, Massachusetts: M.I.T. Press, 1969.
- Sternberg, R.J. Intelligence, information processing, and analogical reasoning: The componential analysis of human abilities. Hillsdale, New Jersey: Erlbaum, 1977.
- Sternberg, R.J. The nature of mental abilities. American Psychologist, 1979, 34, 214-230.
- Tukey, J.W. Exploratory data analysis. Reading, Massachusetts: Addison-Wesley, 1977.
- Yntema, D., & Meuser, C. Keeping track of variables that have few or many states. Journal of Experimental Psychology, 1962, 63, 391-395.

Table 1

Summary of the mappings between observable and unobservable variables
in the easy-to-hard paradigm.

PRIMARY TASK

<u>Equation</u>	<u>Mapping</u>
$p_{1i}(1) = f_1(r_{1i}^*(1), e_{1i}, 1)$	$f_1: E_1 \rightarrow p_1(1)$
$p_{1i}(1+) = f_1((r_{1i}^*(1) - \Delta); e_{1i}, 1)$	$f_1: E_1 \rightarrow p_1(1+)$
$p_{1i}(2) = f_1(R_i, e_{1i}, 2)$	$f_1: E_1 \times R \rightarrow p_1(2)$

SECONDARY TASK

<u>Equation</u>	<u>Mapping</u>
$p_{2i}(0) = f_2(r_{2i}^*, e_{2i}, k)$	$f_2: E_2 \rightarrow p_2(0)$
$p_{2i}(1+) = f_2((R_1 - r_{1i}^*(1) - \Delta), e_{2i}, k)$	$f_2: E_2 \times E_1 \times R \rightarrow p_2(1+)$

Table 2
Sequence of Events for the Paired Associate Task

Event	Display	Duration
Sequential presentation of initial pairs.	A = 7 B = 3	3 sec 3 sec
Question. The correct answer is 3.	B = ?	Subject paced.
Rehearsal interval. Letter just queried is paired with a new number.	B = 4	3 sec
Probe. A probe may occur 500, 1000, or 1500 msec after presentation of a new pair.	(****) B = 4	Probe is presented until subject responds for a maximum of 1500 msec.
Question. The correct answer is 7.	A = ?	Question remains on screen until subject responds.
Rehearsal interval. Letter just queried is paired with a new number.	A = 5	3 sec

Table 3

Correlations between the Target Variable and Three Predictor Variables
in the Paired Associate Task, Experiments 1 and 2 ^a

	First Order Correlations			Partial Correlations		
	<u>Predictor Variable</u>			<u>Predictor Variable: Covariate</u>		
	<u>$p_1(1)$</u>	<u>$p_2(0)$</u>	<u>$p_2(1+)$</u>	<u>$p_2(1+)$: $p_1(1)$</u>	<u>$p_2(1+)$: $p_2(0)$</u>	<u>$p_2(1+)$: $p_1(1), p_2(0)$</u>
<u>Experiment 1</u>						
Paired Associates with Visual Probe, Manual Response	.52	-.05	-.40	-.32	-.44	-.36
<u>Experiment 2</u>						
Paired Associates with Auditory Probe, Vocal Response	.28	-.37	-.39	-.37	-.28	-.28

$p_1(1)$ = Accuracy in the easy paired associate task done alone

$p_2(0)$ = RT in the probe task done alone

$p_2(1+)$ = RT in the probe task during the easy paired associate task

^aCorrelations greater than .27 are significant at the .05 level.

Table 4

Correlations between the Target Variable, and Linear and
Non-Linear Functions of Three Predictor Variables
in the Paired Associate Task, Experiment 3 ^a

	First Order Correlations			Partial Correlations		
	<u>Predictor Variable</u>			<u>Predictor Variable: Covariate</u>		
	<u>$p_1(1)$</u>	<u>$p_2(0)$</u>	<u>$p_2(1+)$</u>	<u>$p_2(1+)$: $p_1(1)$</u>	<u>$p_2(1+)$: $p_2(0)$</u>	<u>$p_2(1+)$: $p_1(1), p_2(0)$</u>
Correlations with the Variable Itself	.57	-.21	-.49	-.30	-.47	-.36
Correlations with a Non-Linear Function of the Variable	.60	-.21	-.49	-.32	-.47	-.31

$p_1(1)$ = Accuracy in the easy paired associate task done alone

$p_2(0)$ = RT in the probe task done alone

$p_2(1+)$ = RT in the probe task during the easy paired associate task

^aCorrelations greater than .22 are significant at the .05 level

Table 5
Correlations between the Target Variable, and Linear and
Non-Linear Functions of Three Predictor Variables^a
in the Spatial Memory Task

	First Order Correlations			Partial Correlations		
	<u>Predictor Variable</u>			<u>Predictor Variable: Covariate</u>		
	<u>$p_1(1)$</u>	<u>$p_2(0)$</u>	<u>$p_2(1+)$</u>	<u>$p_2(1+)$: $p_1(1)$</u>	<u>$p_2(1+)$: $p_2(0)$</u>	<u>$p_2(1+)$: $p_1(1), p_2(0)$</u>
Correlations with the Variable Itself	.27	-.27	-.29	-.23	-.14	-.11
Correlations with a Non-Linear Function of the Variable	.27	.44	-.29	-.22	-.14	-.11

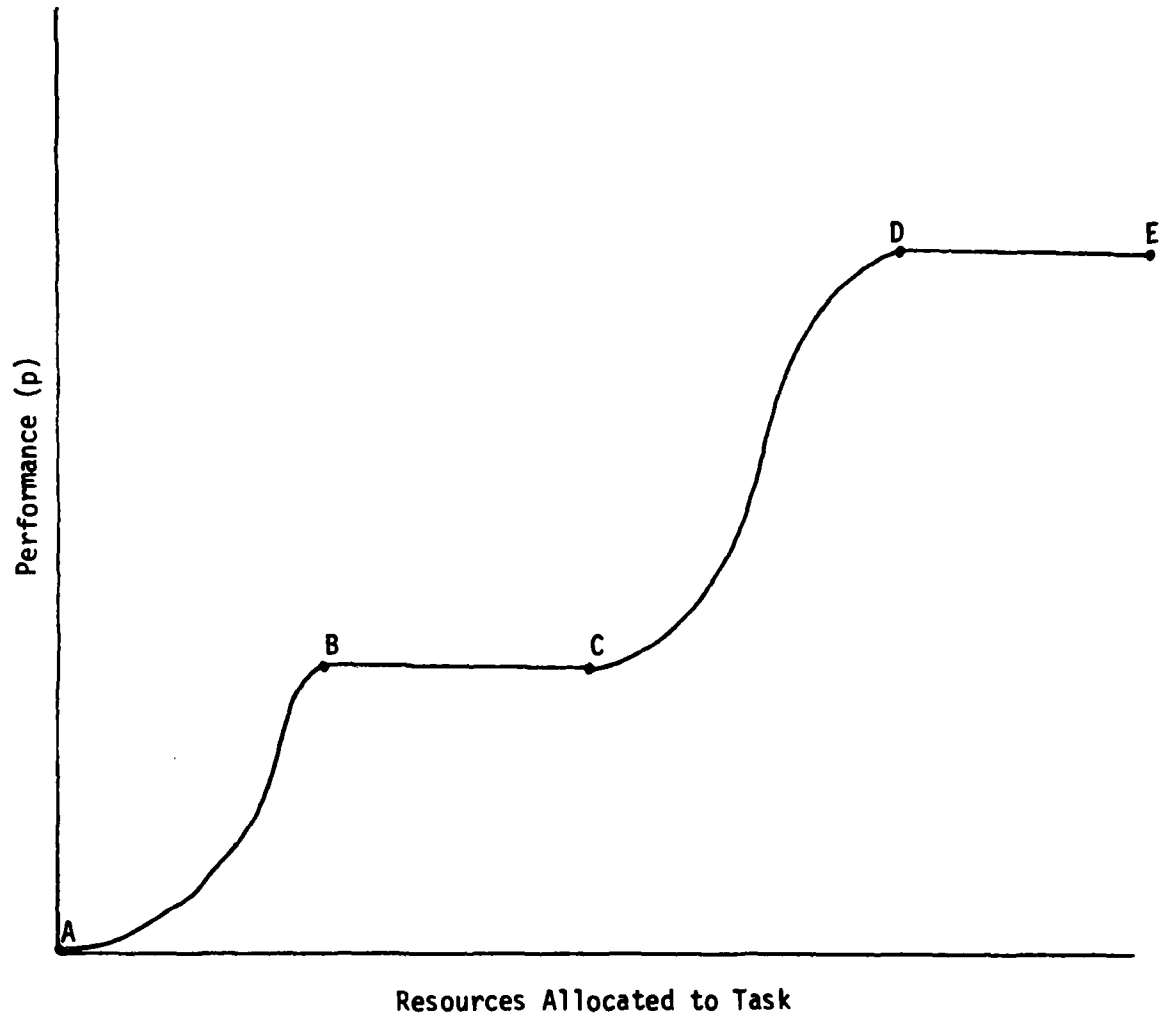
$p_1(1)$ = Accuracy in the easy paired associate task done alone

$p_2(0)$ = RT in the probe task done alone

$p_2(1+)$ = RT in the probe task during the easy paired associate task

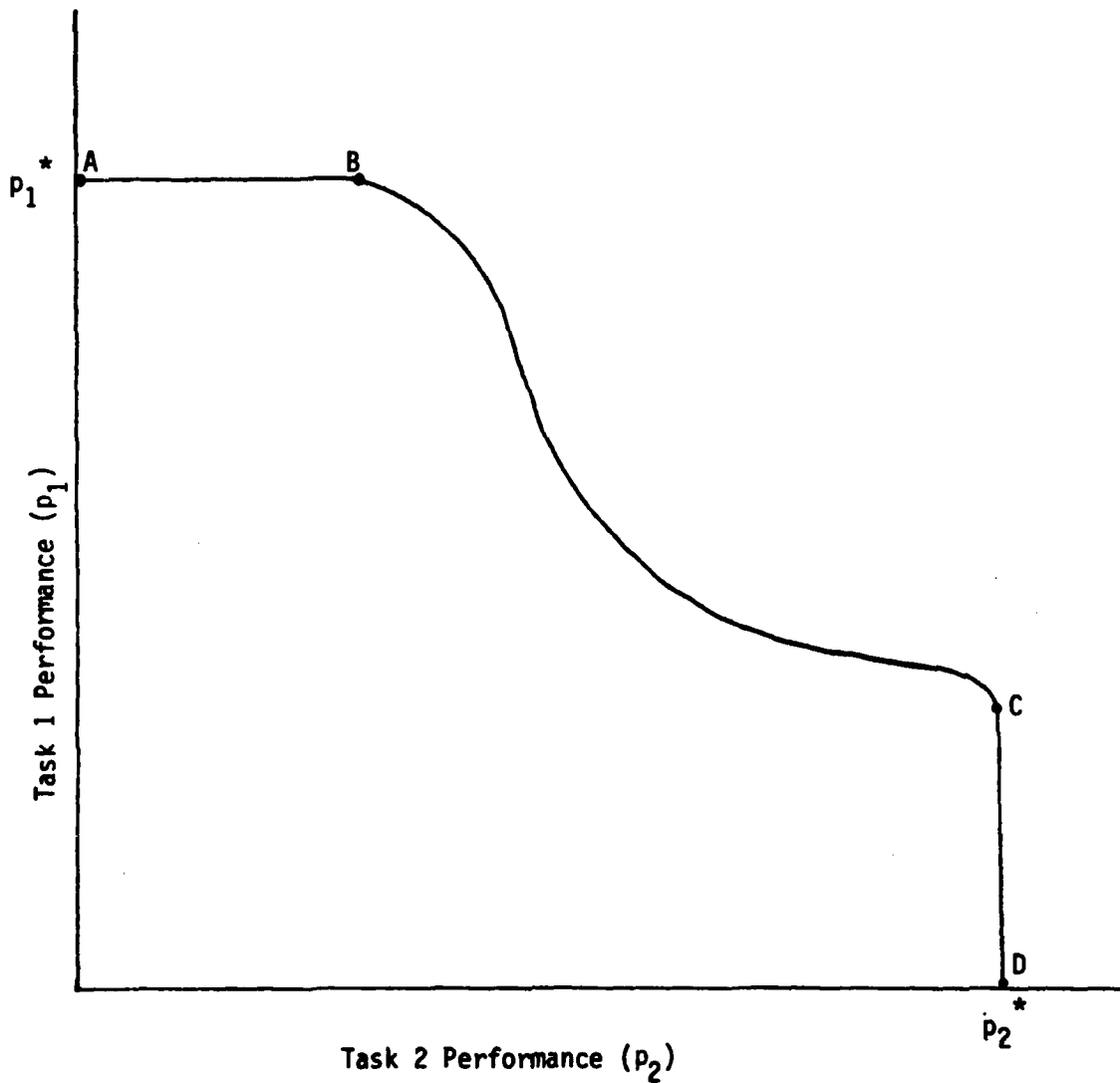
^aCorrelations greater than .22 are significant at the .05 level

Figure 1



A performance-resource function, $p = f(r)$. Performance is resource limited in the regions A to B and C to D, and data limited in the regions B to C and D to E.

Figure 2



A performance operating characteristic (POC) plotting performance on one task as a function of performance on a simultaneously performed task.

Figure 3

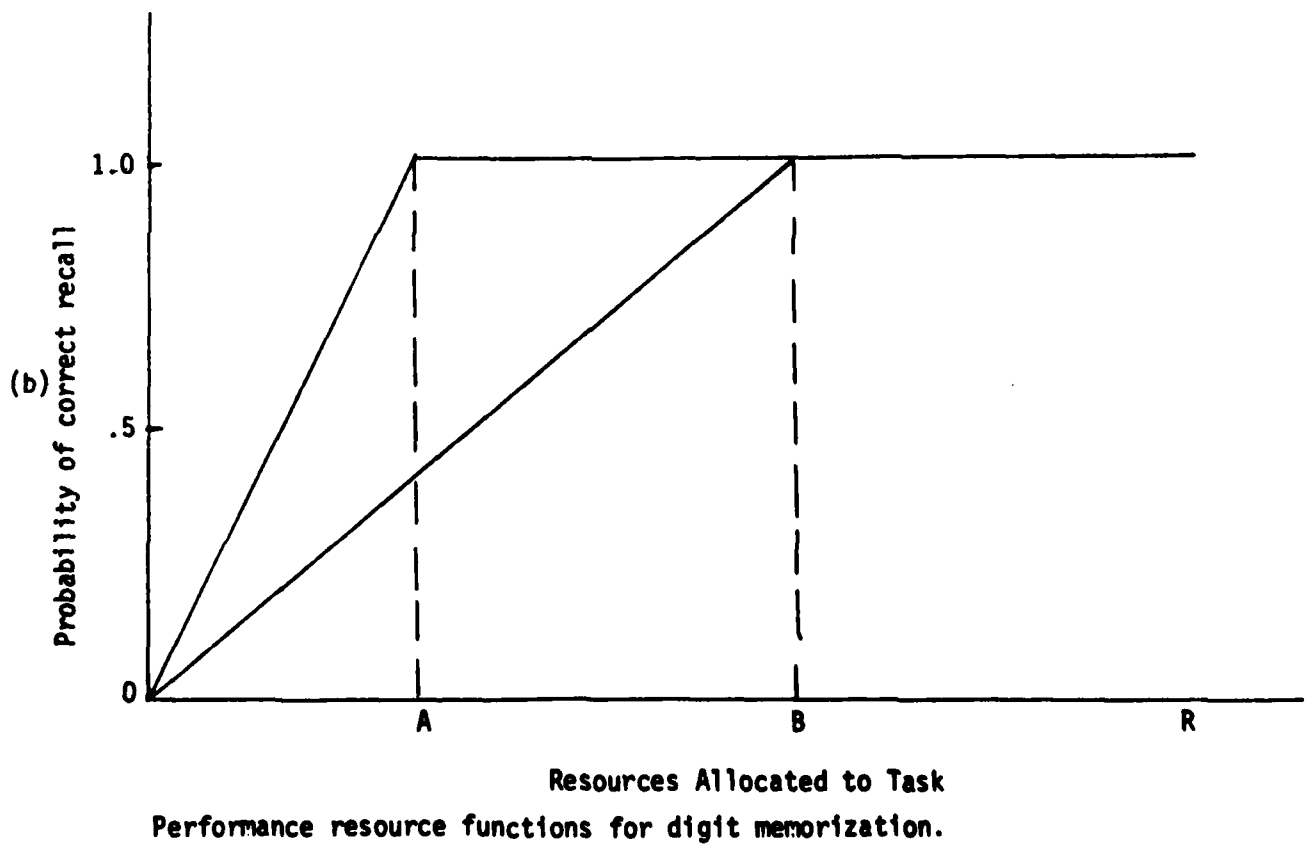
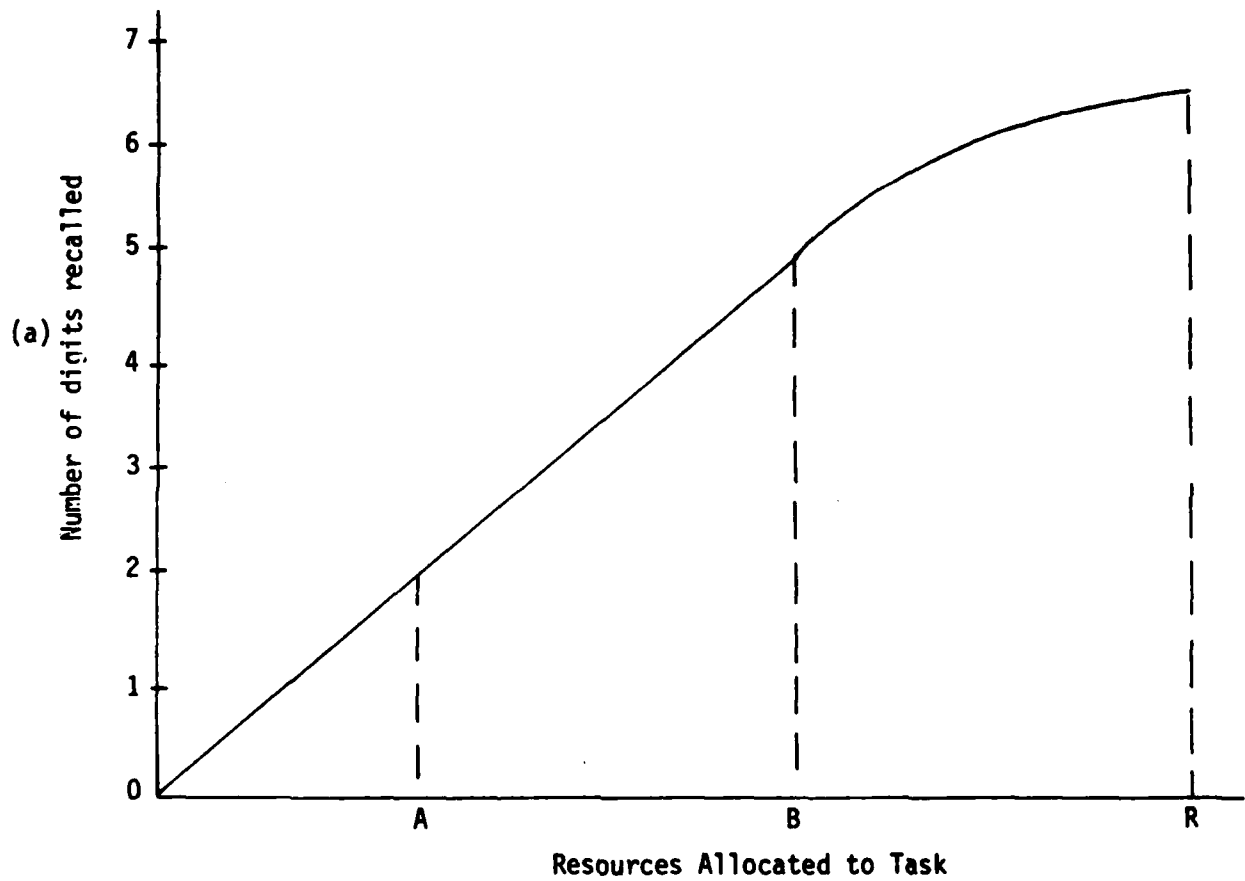
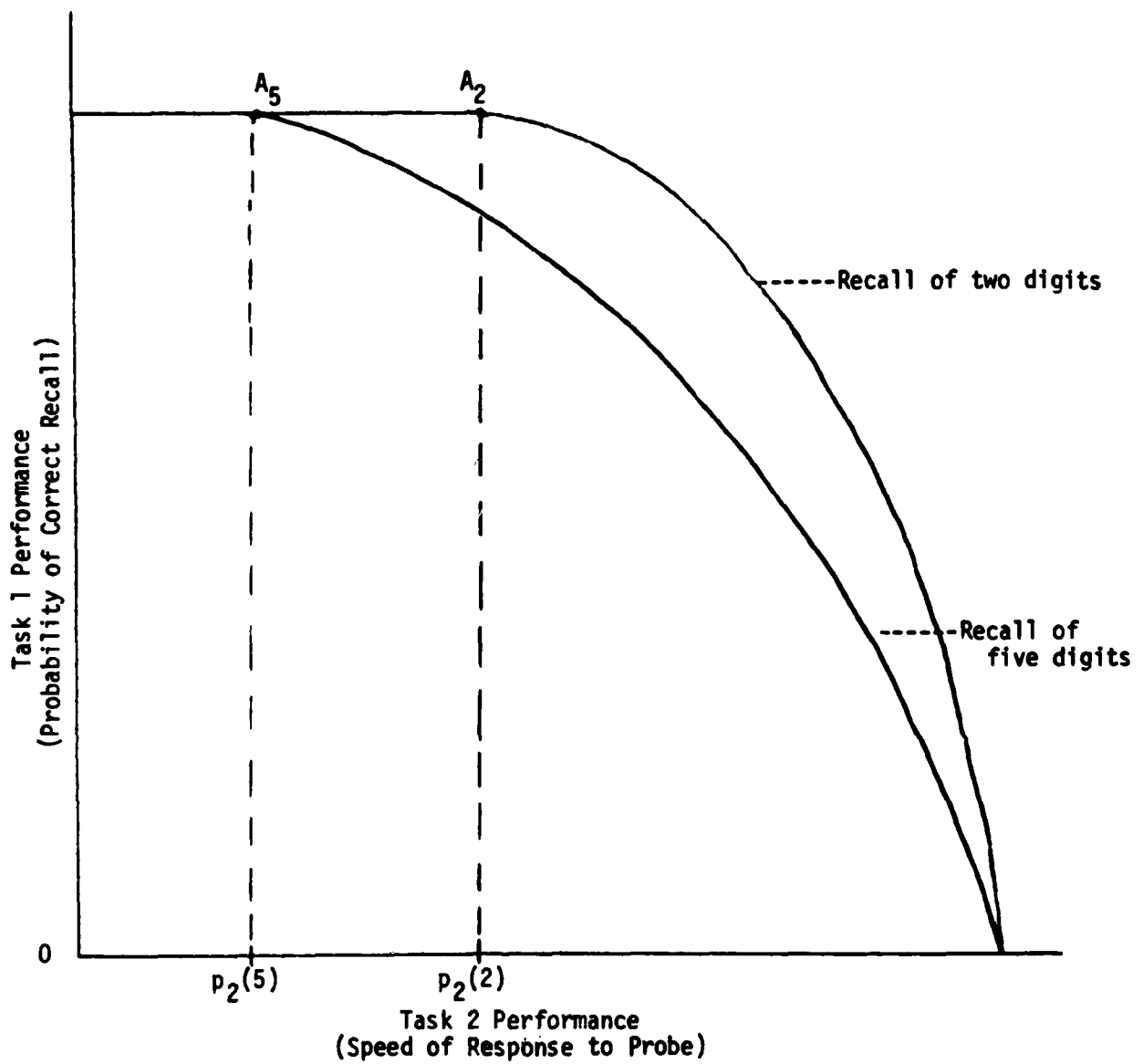
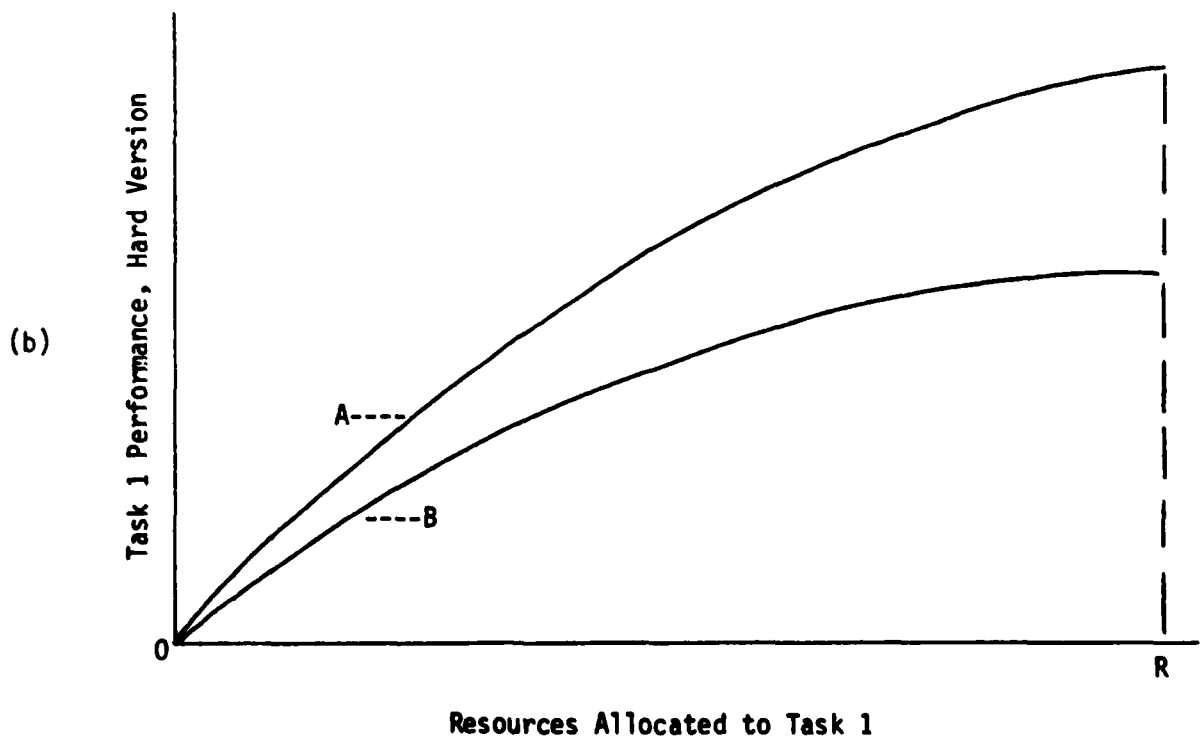
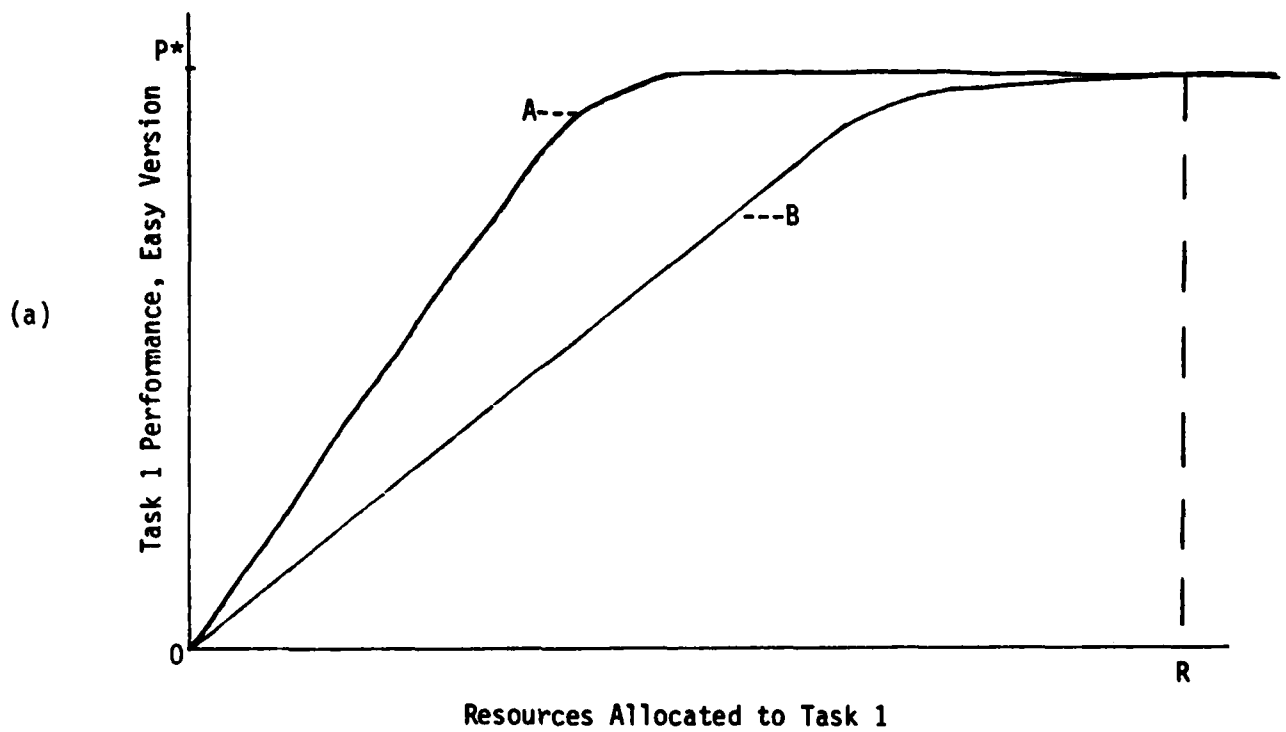


Figure 4



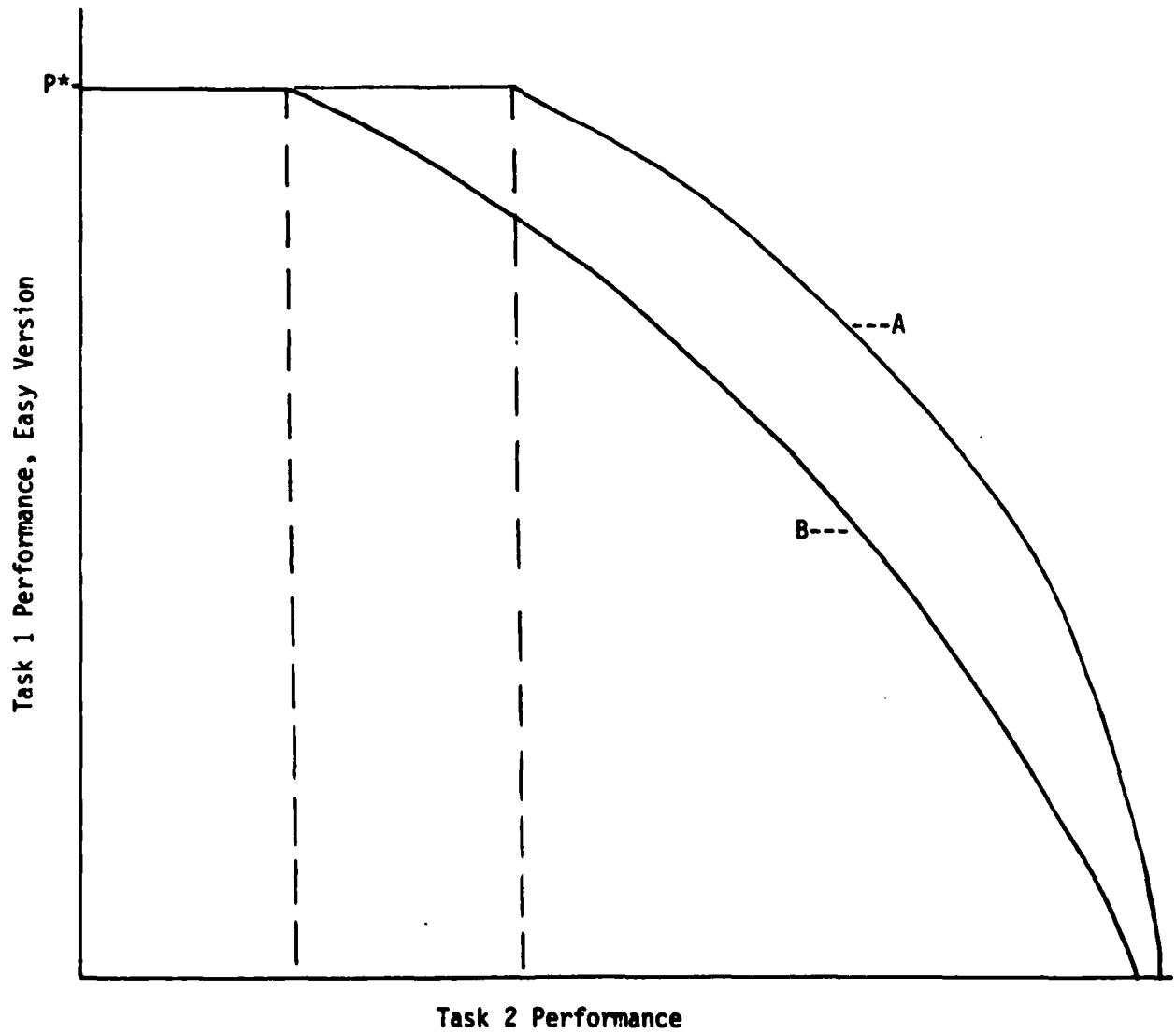
POC for digit recall (primary) and probe reaction time (secondary) tasks under two levels of primary task difficulty.

Figure 5



Performance-resource functions for two subjects, A and B, for Task 1, the primary task.

Figure 6

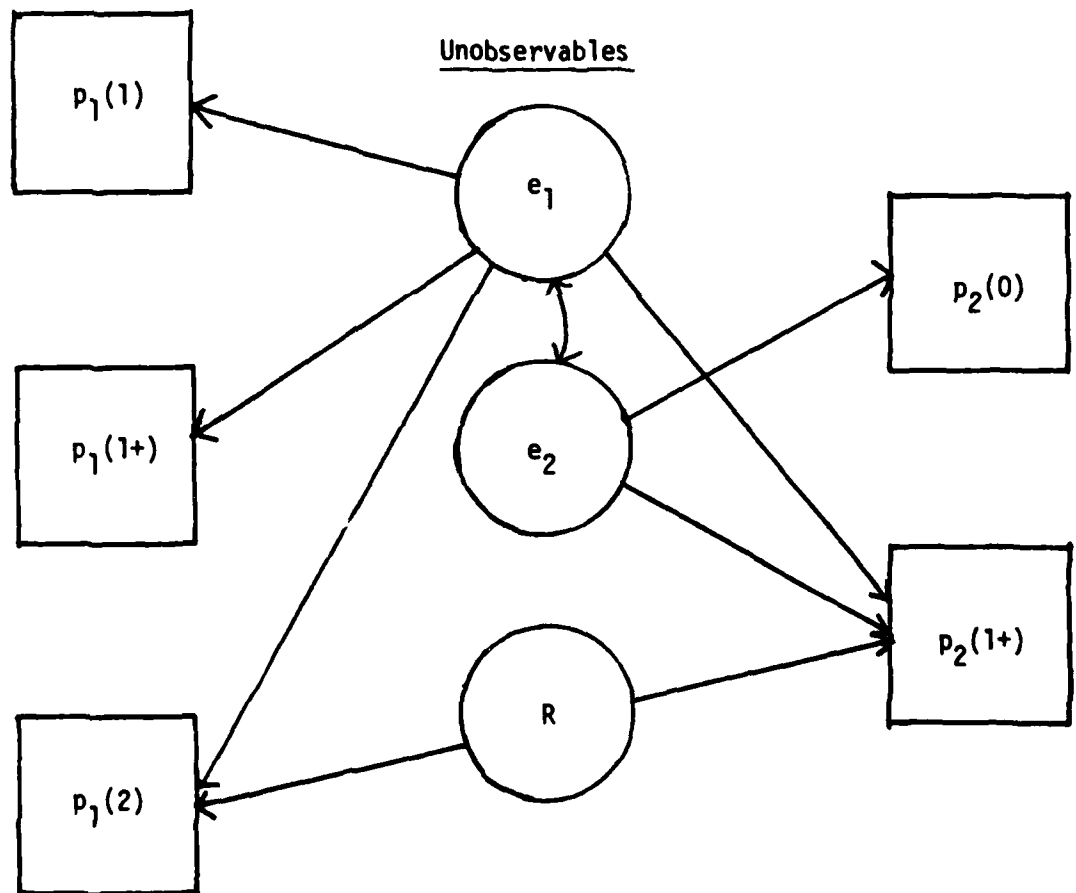


Performance operating characteristics for two subjects, A and B.

Figure 7

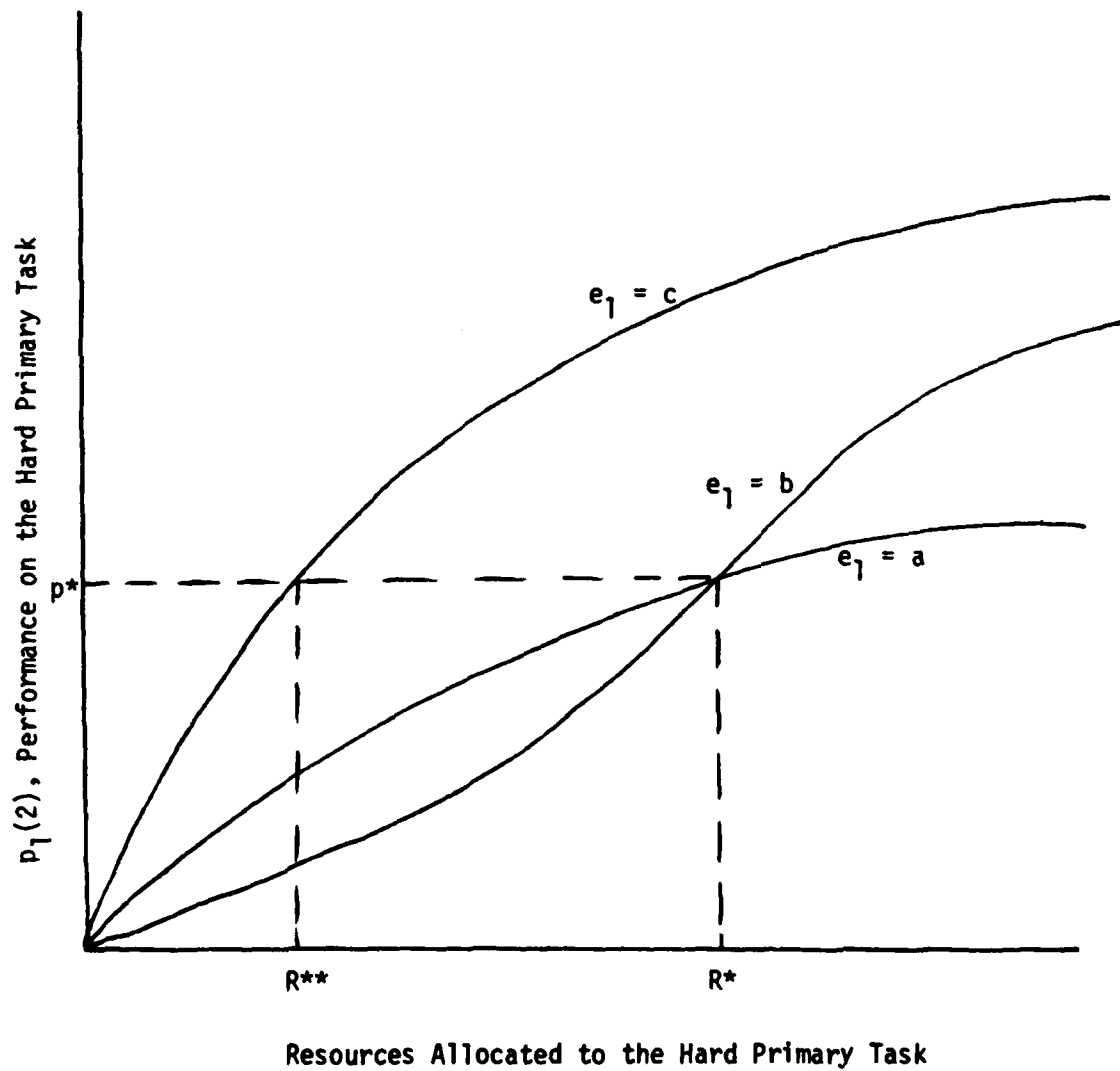
Primary Task Measures

Secondary Task Measures



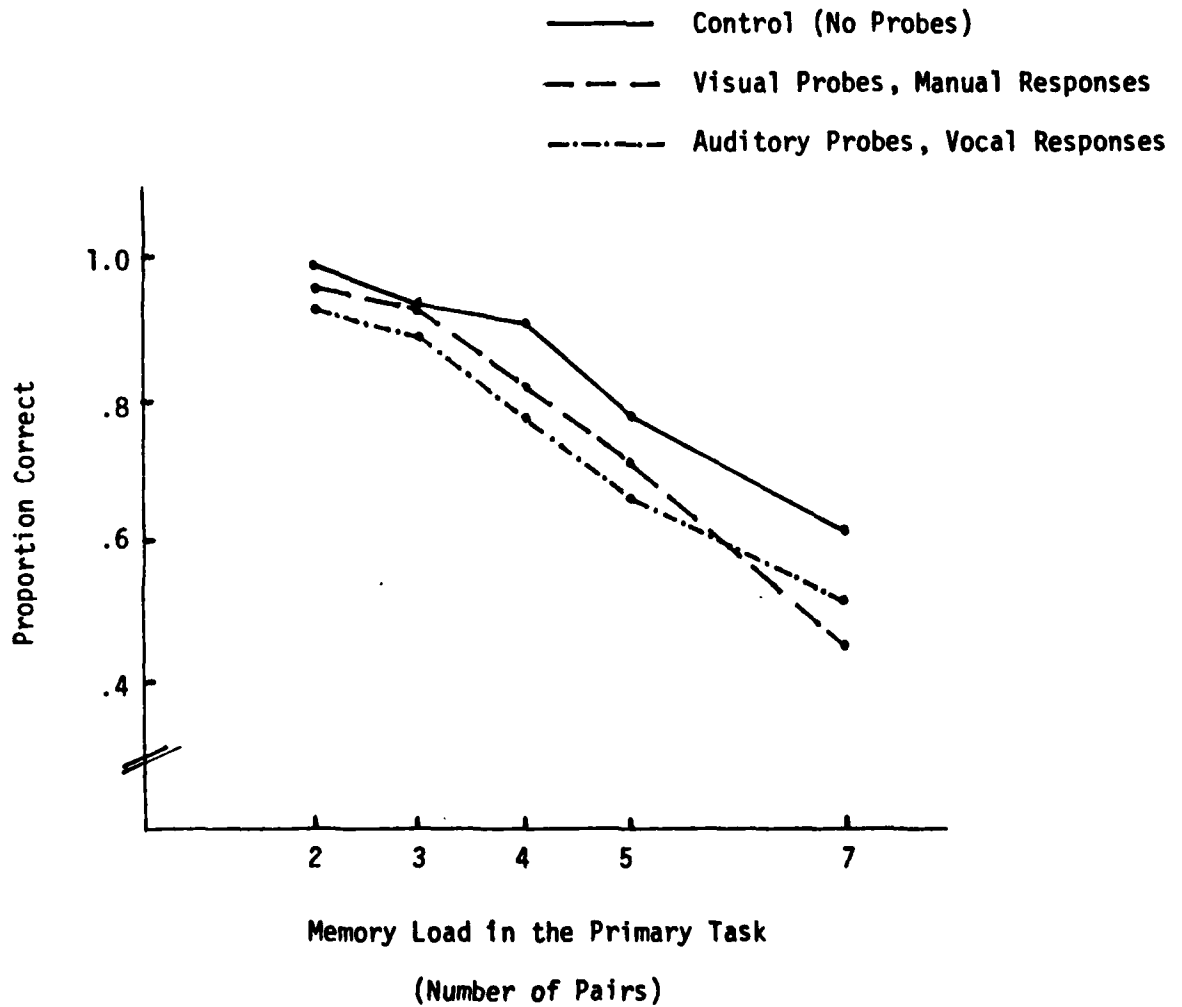
A diagram showing the causal connections between the three unobservable parameters, e_1 , e_2 , and R , and five single and dual-task measures.

Figure 8



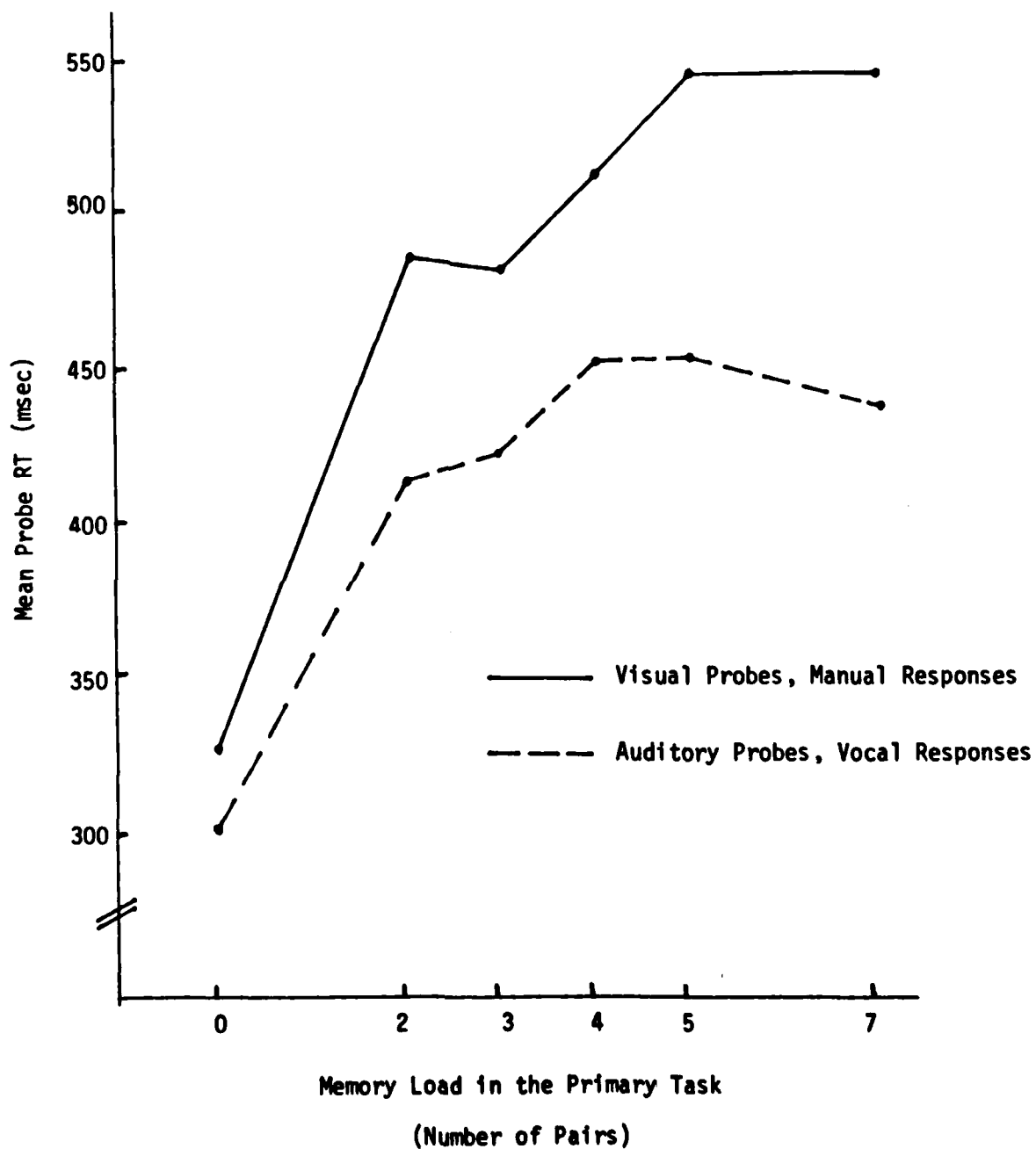
Performance-resource functions illustrating the point that R must be known perfectly, but e_1 may be known only partially, in estimating target variable performance.

Figure 9a



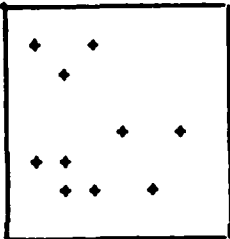
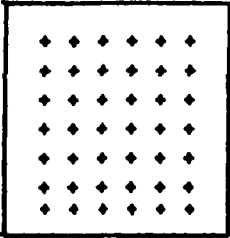
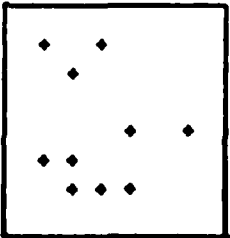
Proportion of paired associate items correctly recalled in single and dual-task conditions as a function of memory load.

Figure 9b



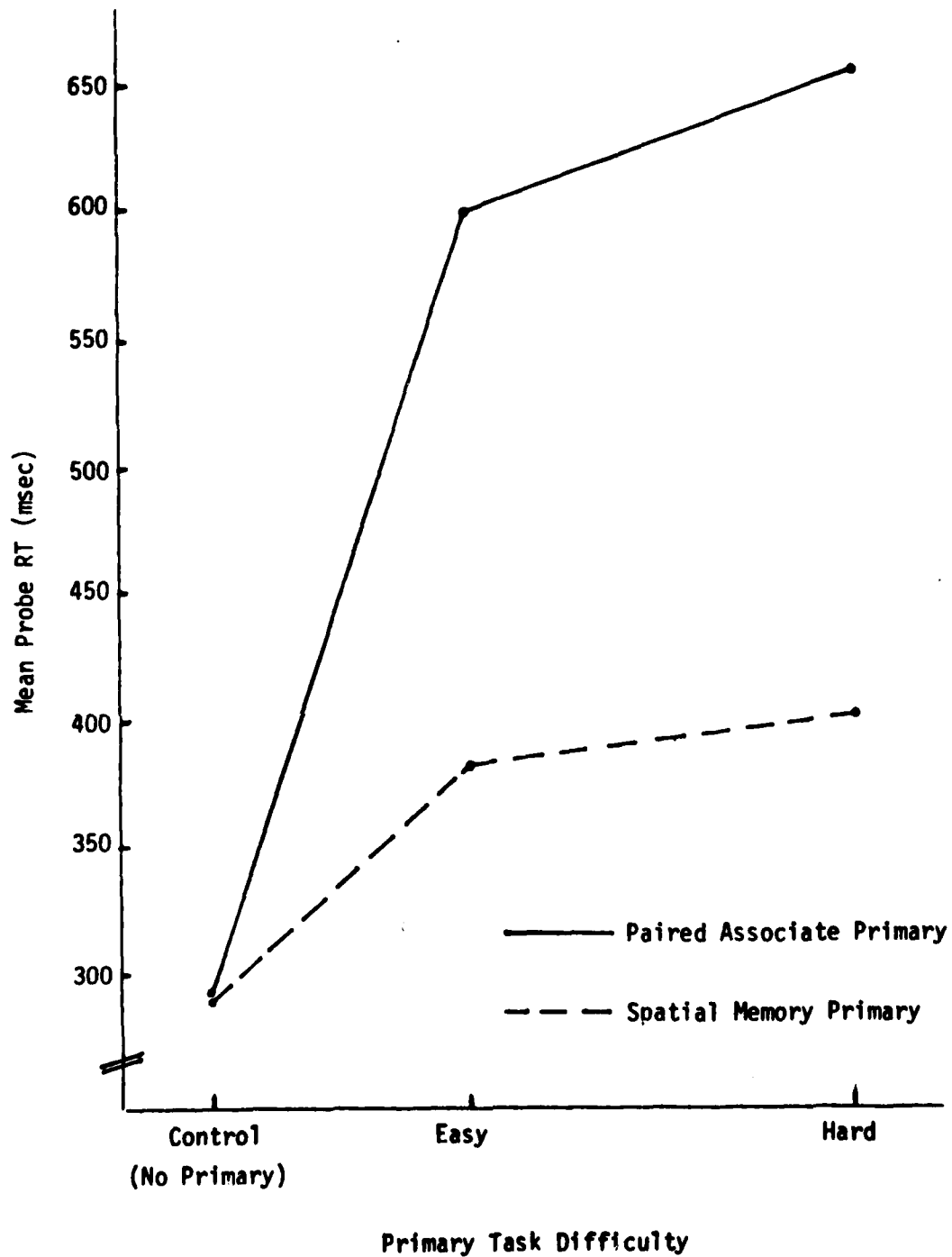
Mean probe RT for the visual-manual and auditory-vocal secondary tasks as a function of memory load in the paired associate primary task.

Figure 10

Event	Display	Duration
<p>Standard pattern. (Probe could occur 500, 1000, or 1500 msec after onset of standard pattern.</p>		<p>3 sec</p>
<p>Mask.</p>		<p>1 sec</p>
<p>Test pattern. Subject responds as to whether test pattern is the same or different from the standard.</p>		<p>Test pattern remains on screen until the subject responds.</p>

Sequence of events in the spatial memory primary task.

Figure 11



Mean probe RT during paired associate and spatial memory primary tasks as a function of primary task difficulty.

Navy

- 1 Dr. Ed Aiken
Navy Personnel R&D Center
San Diego, CA 92152
- 1 Meryl S. Baker
NPRDC
Code P309
San Diego, CA 92152
- 1 Dr. Robert Breaux
Code N-711
NAVTRAEQUIPCEN
Orlando, FL 32813
- 1 Chief of Naval Education and Training
Liason Office
Air Force Human Resource Laboratory
Flying Training Division
WILLIAMS AFB, AZ 85224
- 1 COMNAVMILPERSCOM (N-6C)
Dept. of Navy
Washington, DC 20370
- 1 Dr. Richard Elster
Department of Administrative Sciences
Naval Postgraduate School
Monterey, CA 93940
- 1 DR. PAT FEDERICO
NAVY PERSONNEL R&D CENTER
SAN DIEGO, CA 92152
- 1 Mr. Paul Foley
Navy Personnel R&D Center
San Diego, CA 92152
- 1 Dr. John Ford
Navy Personnel R&D Center
San Diego, CA 92152
- 1 Dr. Richard Gibson
Bureau of medicine and surgery
Code 3C13
Navy Department
Washington, DC 20372

Navy

- 1 Dr. Henry M. Halff
Department of Psychology, C-009
University of California at San Diego
La Jolla, CA 92093
- 1 LT Steven D. Harris, MSC, USN
Code 6021
Naval Air Development Center
Warminster, Pennsylvania 18974
- 1 Dr. Patrick R. Harrison
Psychology Course Director
LEADERSHIP & LAW DEPT. (7b)
DIV. OF PROFESSIONAL DEVELOPMENT
U.S. NAVAL ACADEMY
ANNAPOLIS, MD 21402
- 1 CDR Charles W. Hutchins
Naval Air Systems Command Hq
AIR-340F
Navy Department
Washington, DC 20361
- 1 CDR Robert S. Kennedy
Head, Human Performance Sciences
Naval Aerospace Medical Research Lab
Box 29407
New Orleans, LA 70189
- 1 Dr. Norman J. Kerr
Chief of Naval Technical Training
Naval Air Station Memphis (75)
Millington, TN 38054
- 1 Dr. William L. Maloy
Principal Civilian Advisor for
Education and Training
Naval Training Command, Code 00A
Pensacola, FL 32508
- 1 Dr. Kneale Marshall
Scientific Advisor to DCNO(MPT)
OP01T
Washington DC 20370

Navy	Navy
1 CAPT Richard L. Martin, USN Prospective Commanding Officer USS Carl Vinson (CVN-70) Newport News Shipbuilding and Drydock Co Newport News, VA 23607	1 Psychologist ONR Branch Office Bldg 114, Section D 666 Summer Street Boston, MA 02210
1 Dr William Montague Navy Personnel R&D Center San Diego, CA 92152	1 Psychologist ONR Branch Office 536 S. Clark Street Chicago, IL 60605
1 Commanding Officer U.S. Naval Amphibious School Coronado, CA 92155	1 Office of Naval Research Code 437 800 N. Quincy Street Arlington, VA 22217
1 Library Naval Health Research Center P. O. Box 85122 San Diego, CA 92138	1 Office of Naval Research Code 441 800 N. Quincy Street Arlington, VA 22217
1 Naval Medical R&D Command Code 44 National Naval Medical Center Bethesda, MD 20014	5 Personnel & Training Research Programs (Code 458) Office of Naval Research Arlington, VA 22217
1 CAPT Paul Nelson, USN Chief, Medical Service Corps Bureau of Medicine & Surgery (MED-23) U. S. Department of the Navy Washington, DC 20372	1 Psychologist ONR Branch Office 1030 East Green Street Pasadena, CA 91101
1 Ted M. I. Yellen Technical Information Office, Code 201 NAVY PERSONNEL R&D CENTER SAN DIEGO, CA 92152	1 Office of the Chief of Naval Operations Research Development & Studies Branch (OP-115) Washington, DC 20350
1 Library, Code P201L Navy Personnel R&D Center San Diego, CA 92152	1 LT Frank C. Petho, MSC, USN (Ph.D) Code L51 Naval Aerospace Medical Research Laborat Pensacola, FL 32508
1 Technical Director Navy Personnel R&D Center San Diego, CA 92152	1 Roger W. Remington, Ph.D Code L52 NAMRL Pensacola, FL 32508
6 Commanding Officer Naval Research Laboratory Code 2627 Washington, DC 20390	1 Dr. Bernard Rimland (03B) Navy Personnel R&D Center San Diego, CA 92152

Navy

- 1 Mr. Arnold Rubenstein
Naval Personnel Support Technology
Naval Material Command (NST244)
Room 1044, Crystal Plaza #5
2221 Jefferson Davis Highway
Arlington, VA 20360
- 1 Dr. Worth Scanland
Chief of Naval Education and Training
Code N-5
NAS, Pensacola, FL 32508
- 1 Dr. Robert G. Smith
Office of Chief of Naval Operations
OP-987H
Washington, DC 20350
- 1 Dr. Alfred F. Snode
Training Analysis & Evaluation Group
(TAEG)
Dept. of the Navy
Orlando, FL 32813
- 1 Dr. Richard Sorensen
Navy Personnel R&D Center
San Diego, CA 92152
- 1 W. Gary Thomson
Naval Ocean Systems Center
Code 7132
San Diego, CA 92152
- 1 Dr. Robert Wisher
Code 309
Navy Personnel R&D Center
San Diego, CA 92152
- 1 DR. MARTIN F. WISKOFF
NAVY PERSONNEL R&D CENTER
SAN DIEGO, CA 92152

Army

- 1 HQ USAREUE & 7th Army
ODCSOPS
USAAREUE Director of GED
APO New York 09403
- 1 DR. RALPH DUSEK
U.S. ARMY RESEARCH INSTITUTE
5001 EISENHOWER AVENUE
ALEXANDRIA, VA 22333
- 1 Dr. Myron Fischl
U.S. Army Research Institute for the
Social and Behavioral Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333
- 1 DR. FRANK J. HARRIS
U.S. ARMY RESEARCH INSTITUTE
5001 EISENHOWER AVENUE
ALEXANDRIA, VA 22333
- 1 Col Frank Hart
Army Research Institute for the
Behavioral & Social Sciences
5001 Eisenhower Blvd.
Alexandria, VA 22333
- 1 Dr. Michael Kaplan
U.S. ARMY RESEARCH INSTITUTE
5001 EISENHOWER AVENUE
ALEXANDRIA, VA 22333
- 1 Dr. Milton S. Katz
Training Technical Area
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333
- 1 Dr. Harold F. O'Neil, Jr.
Attn: PERI-OK
Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333
- 1 Dr. Robert Sasmor
U. S. Army Research Institute for the
Behavioral and Social Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

Army

- 1 Commandant
US Army Institute of Administration
Attn: Dr. Sherrill
FT Benjamin Harrison, IN 46256
- 1 Dr. Frederick Steinheiser
U. S. Army Reserch Institute
5001 Eisenhower Avenue
Alexandria, VA 22333
- 1 Dr. Joseph Ward
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Air Force

- 1 Dr. Earl A. Alluisi
HQ, AFHRL (AFSC)
Brooks AFB, TX 78235
- 1 Dr. Genevieve Haddad
Program Manager
Life Sciences Directorate
AFOSR
Bolling AFB, DC 20332
- 1 Dr. Ross L. Morgan (AFHRL/LR)
Wright -Patterson AFB
Ohio 45433
- 1 Research and Measurment Division
Research Branch, AFMPC/MPCYPR
Randolph AFB, TX 78148
- 1 Dr. Marty Rockway (AFHRL/TT)
Lowry AFB
Colorado 80230
- 1 Jack A. Thorpe, Maj., USAF
Naval War College
Providence, RI 02846

Marines

- 1 Director, Office of Manpower Utilization 12
HQ, Marine Corps (MPU)
BCB, Bldg. 2009
Quantico, VA 22134
- 1 DR. A.L. SLAFKOSKY
SCIENTIFIC ADVISOR (CODE RD-1)
HQ, U.S. MARINE CORPS
WASHINGTON, DC 20380

Other DoD

- Defense Technical Information Center
Cameron Station, Bldg 5
Alexandria, VA 22314
Attn: TC
- 1 Dr. Craig I. Fields
Advanced Research Projects Agency
1400 Wilson Blvd.
Arlington, VA 22209
- 1 Dr. Dexter Fletcher
ADVANCED RESEARCH PROJECTS AGENCY
1400 WILSON BLVD.
ARLINGTON, VA 22209
- 1 Military Assistant for Training and
Personnel Technology
Office of the Under Secretary of Defense
for Research & Engineering
Room 3D129, The Pentagon
Washington, DC 20301
- 1 HEAD, SECTION ON MEDICAL EDUCATION
UNIFORMED SERVICES UNIV. OF THE
HEALTH SCIENCES
6917 ARLINGTON ROAD
BETHESDA, MD 20014

Civil Govt

- 1 Dr. Susan Chipman
Learning and Development
National Institute of Education
1200 19th Street NW
Washington, DC 20208
- 1 Dr. Joseph I. Lipson
SEDR W-638
National Science Foundation
Washington, DC 20550
- 1 Dr. John Mays
National Institute of Education
1200 19th Street NW
Washington, DC 20208
- 1 Dr. Arthur Melmed
National Institute of Education
1200 19th Street NW
Washington, DC 20208
- 1 Dr. H. Wallace Sinaiko
Program Director
Manpower Research and Advisory Services
Smithsonian Institution
801 North Pitt Street
Alexandria, VA 22314
- 1 Dr. Joseph L. Young, Director
Memory & Cognitive Processes
National Science Foundation
Washington, DC 20550

Non Govt

- 1 Dr. John R. Anderson
Department of Psychology
Carnegie Mellon University
Pittsburgh, PA 15213
- 1 DR. MICHAEL ATWOOD
SCIENCE APPLICATIONS INSTITUTE
40 DENVER TECH. CENTER WEST
7935 E. PRENTICE AVENUE
ENGLEWOOD, CO 80110
- 1 1 psychological research unit
Dept. of Defense (Army Office)
Campbell Park Offices
Canberra ACT 2600, Australia
- 1 Dr. Alan Baddeley
Medical Research Council
Applied Psychology Unit
15 Chaucer Road
Cambridge CB2 2EF
ENGLAND
- 1 Dr. Jackson Beatty
Department of Psychology
University of California
Los Angeles, CA 90024
- 1 Dr. Isaac Bejar
Educational Testing Service
Princeton, NJ 08450
- 1 Dr. Nicholas A. Bond
Dept. of Psychology
Sacramento State College
600 Jay Street
Sacramento, CA 95819
- 1 Dr. Lyle Bourne
Department of Psychology
University of Colorado
Boulder, CO 80309
- 1 Dr. John S. Brown
XEROX Palo Alto Research Center
3333 Coyote Road
Palo Alto, CA 94304

Non Govt

- 1 Dr. Pat Carpenter
Department of Psychology
Carnegie-Mellon University
Pittsburgh, PA 15213
- 1 Dr. John B. Carroll
Psychometric Lab
Univ. of No. Carolina
Davie Hall 013A
Chapel Hill, NC 27514
- 1 Charles Myers Library
Livingstone House
Livingstone Road
Stratford
London E15 2LJ
ENGLAND
- 1 Dr. William Chase
Department of Psychology
Carnegie Mellon University
Pittsburgh, PA 15213
- 1 Dr. Micheline Chi
Learning R & D Center
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15213
- 1 Dr. Allan M. Collins
Bolt Beranek & Newman, Inc.
50 Moulton Street
Cambridge, Ma 02138
- 1 Dr. Lynn A. Cooper
Department of psychology
Uris Hall
Cornell University
Ithaca, NY 14850
- 1 Dr. Meredith P. Crawford
American Psychological Association
1200 17th Street, N.W.
Washington, DC 20036
- 1 Dr. Kenneth B. Cross
Anacapa Sciences, Inc.
P.O. Drawer Q
Santa Barbara, CA 93102

Non Govt

- 1 Dr. Emmanuel Donchin
Department of Psychology
University of Illinois
Champaign, IL 61820
- 1 Dr. Hubert Dreyfus
Department of Philosophy
University of California
Berkely, CA 94720
- 1 LCOL J. C. Eggenberger
DIRECTORATE OF PERSONNEL APPLIED RESEARCH
NATIONAL DEFENCE HQ
101 COLONEL BY DRIVE
OTTAWA, CANADA K1A 0K2
- 1 Dr. Ed Feigenbaum
Department of Computer Science
Stanford University
Stanford, CA 94305
- 1 Dr. Victor Fields
Dept. of Psychology
Montgomery College
Rockville, MD 20850
- 1 Dr. Edwin A. Fleishman
Advanced Research Resources Organ.
Suite 900
4330 East West Highway
Washington, DC 20014
- 1 Dr. John R. Frederiksen
Bolt Beranek & Newman
50 Moulton Street
Cambridge, MA 02138
- 1 Dr. Alinda Friedman
Department of Psychology
University of Alberta
Edmonton, Alberta
CANADA T6G 2E9
- 1 Dr. R. Edward Geiselman
Department of Psychology
University of California
Los Angeles, CA 90024

Non Govt

- 1 DR. ROBERT GLASER
LRDC
UNIVERSITY OF PITTSBURGH
3939 O'HARA STREET
PITTSBURGH, PA 15213
- 1 DR. JAMES G. GREENO
LRDC
UNIVERSITY OF PITTSBURGH
3939 O'HARA STREET
PITTSBURGH, PA 15213
- 1 Dr. Harold Hawkins
Department of Psychology
University of Oregon
Eugene OR 97403
- 1 Dr. Barbara Hayes-Roth
The Rand Corporation
1700 Main Street
Santa Monica, CA 90406
- 1 Dr. Frederick Hayes-Roth
The Rand Corporation
1700 Main Street
Santa Monica, CA 90406
- 1 Mr. Richards J. Heuer, Jr.
27585 Via Sereno
Carmel, CA 92923
- 1 Dr. James R. Hoffman
Department of Psychology
University of Delaware
Newark, DE 19711
- 1 Dr. Lloyd Humphreys
Department of Psychology
University of Illinois
Champaign, IL 61820
- 1 Dr. Steven W. Keele
Dept. of Psychology
University of Oregon
Eugene, OR 97403

Non Govt

- 1 Dr. Walter Kintsch
Department of Psychology
University of Colorado
Boulder, CO 80302
- 1 Dr. David Kieras
Department of Psychology
University of Arizona
Tucson, AZ 85721
- 1 Dr. Kenneth A. Klivington
Program Officer
Alfred P. Sloan Foundation
630 Fifth Avenue
New York, NY 10111
- 1 Dr. Mazie Knerr
Litton-Mellonics
Box 1286
Springfield, VA 22151
- 1 Dr. Stephen Kosslyn
Harvard University
Department of Psychology
33 Kirkland Street
Cambridge, MA 02138
- 1 Mr. Marlin Kroger
1117 Via Goleta
Palos Verdes Estates, CA 90274
- 1 Dr. Jill Larkin
Department of Psychology
Carnegie Mellon University
Pittsburgh, PA 15213
- 1 Dr. Alan Lesgold
Learning R&D Center
University of Pittsburgh
Pittsburgh, PA 15260
- 1 Dr. Mark Miller
Computer Science Laboratory
Texas Instruments, Inc.
Mail Station 371, P.O. Box 225936
Dallas, TX 75265

Non Govt

- 1 Dr. Allen Munro
Behavioral Technology Laboratories
1845 Elena Ave., Fourth Floor
Redondo Beach, CA 90277
- 1 Dr. Donald A Norman
Dept. of Psychology C-009
Univ. of California, San Diego
La Jolla, CA 92093
- 1 Dr. Melvin R. Novick
356 Lindquist Center for Measurement
University of Iowa
Iowa City, IA 52242
- 1 Dr. Jesse Orlansky
Institute for Defense Analyses
400 Army Navy Drive
Arlington, VA 22202
- 1 MR. LUIGI PETRULLO
2431 N. EDGEWOOD STREET
ARLINGTON, VA 22207
- 1 Dr. Martha Polson
Department of Psychology
University of Colorado
Boulder, CO 80302
- 1 DR. PETER POLSON
DEPT. OF PSYCHOLOGY
UNIVERSITY OF COLORADO
BOULDER, CO 80309
- 1 DR. DIANE M. RAMSEY-KLEE
R-K RESEARCH & SYSTEM DESIGN
3947 RIDGEMONT DRIVE
MALIBU, CA 90265
- 1 Dr. Fred Reif
SESAME
c/o Physics Department
University of California
Berkeley, CA 94720
- 1 Dr. Andrew M. Rose
American Institutes for Research
1055 Thomas Jefferson St. NW
Washington, DC 20007

Non Govt

- 1 Dr. Ernst Z. Rothkopf
Bell Laboratories
600 Mountain Avenue
Murray Hill, NJ 07974
- 1 Dr. David Rumelhart
Center for Human Information Processing
Univ. of California, San Diego
La Jolla, CA 92093
- 1 PROF. FUMIKO SAMEJIMA
DEPT. OF PSYCHOLOGY
UNIVERSITY OF TENNESSEE
KNOXVILLE, TN 37916
- 1 DR. WALTER SCHNEIDER
DEPT. OF PSYCHOLOGY
UNIVERSITY OF ILLINOIS
CHAMPAIGN, IL 61820
- 1 DR. ROBERT J. SEIDEL
INSTRUCTIONAL TECHNOLOGY GROUP
HUMRRO
300 N. WASHINGTON ST.
ALEXANDRIA, VA 22314
- 1 Dr. Richard Snow
School of Education
Stanford University
Stanford, CA 94305
- 1 Dr. Robert Sternberg
Dept. of Psychology
Yale University
Box 11A, Yale Station
New Haven, CT 06520
- 1 DR. ALBERT STEVENS
BOLT BERANEK & NEWMAN, INC.
50 MOULTON STREET
CAMBRIDGE, MA 02138
- 1 Dr. David Stone
ED 236
SUNY, Albany
Albany, NY 12222

Non Govt

- 1 DR. PATRICK SUPPES
INSTITUTE FOR MATHEMATICAL STUDIES IN
THE SOCIAL SCIENCES
STANFORD UNIVERSITY
STANFORD, CA 94305
- 1 Dr. Kikumi Tatsuoka
Computer Based Education Research
Laboratory
252 Engineering Research Laboratory
University of Illinois
Urbana, IL 61801
- 1 DR. PERRY THORNDYKE
THE RAND CORPORATION
1700 MAIN STREET
SANTA MONICA, CA 90406
- 1 Dr. Douglas Towne
Univ. of So. California
Behavioral Technology Labs
1845 S. Elena Ave.
Redondo Beach, CA 90277
- 1 Dr. J. Uhlaner
Perceptrics, Inc.
6271 Variel Avenue
Woodland Hills, CA 91364
- 1 Dr. Benton J. Underwood
Dept. of Psychology
Northwestern University
Evanston, IL 60201
- 1 Dr. Phyllis Weaver
Graduate School of Education
Harvard University
200 Larsen Hall, Appian Way
Cambridge, MA 02138
- 1 Dr. David J. Weiss
N660 Elliott Hall
University of Minnesota
75 E. River Road
Minneapolis, MN 55455

Non Govt

- 1 Dr. Keith T. Wescourt
Information Sciences Dept.
The Rand Corporation
1700 Main St.
Santa Monica, CA 90406
- 1 Dr. J. Arthur Woodward
Department of Psychology
University of California
Los Angeles, CA 90024

**DATE
FILMED**

2-8